Three Essays on the Consequences of Financial Market Frictions

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INTRODUCTION

This PhD dissertation studies the consequences of capital market imperfections, with the objective of understanding both their direct effects on the market where they are generated, but also their spillover effects on related markets. While one core assumption behind neoclassical asset pricing theories is that capital can always flow without frictions to the most productive investment opportunities, this is in practice not the case. In the presence of frictions, asset prices and the allocation of credit might behave quite differently from what neoclassical theory predicts, at least temporarily. This leads to distortions in prices and in the volumes invested, which might affect related markets as well as real outcomes.

The following three essays focus on the role of financial intermediaries in generating these misallocations. It is indeed fascinating how a relatively small group of firms and institutions at the core of our financial systems can generate externalities that affect the whole economy. The first essay studies how capital inflows can lead to a less efficient allocation of talent, when the inflows are channelled through a weak financial sector. The second essay studies the spillover effects on the bond market of a change in the composition of a highly concentrated dealer market in credit derivatives. And the third essay investigates how bank private information on corporate customers affects trading and price discovery in the less transparent over-the-counter dealer market.

The research designs employed exploit exogenous shocks to investigate these spillover effects and to estimate the resulting distortions. The sources of data include the credit register, firm financials, and a labour census available at Bank of Portugal, as well as with security holding statistics and transaction-level data on derivative markets, available at the Deutsche Bundesbank and at the European Central Bank.

The title of the first essay is **'Capital Inflows, Credit Growth, and Skill Misallocation'**. In this work, my co-authors Claire Celerier, Luciana Barbosa, and I study whether large capital inflows lead to the misallocation of high-skill workers. Gopinath et al. (2017) show that large capital inflows can lead to a decrease in the allocative efficiency of capital. We combine a comprehensive credit register with a worker level census and show that large capital inflows can also lead to the misallocation of talent.

Our investigation is set up in Portugal in 2004-2006, a period when the country experienced large capital inflows due to the integration to the Euro area. These capital inflows where channelled through the banking sector. In this setting, we exploit exogenous variations in the Portuguese banks' ability to channel capital inflows. More precisely, a shock to the valuation of pension liabilities of a group of banks reduces the equity and capital of these banks. Credit growth at affected banks slows down. We then study whether firms associated with affected banks have a different employment behaviour than firms associated with the remaining banks. We show that not only leverage, but also employment and skill-intensity increase in the firms associated with unaffected banks, that is, banks which were able to channel capital flows without restriction. The effects are stronger in the less productive, nontradable sector. Our results suggest that capital and skills can concentrate in the less productive firms and sectors in periods of abundant capital inflows, potentially dampening long-run productivity growth.

The second essay, **'CDS Market Liquidity and Bond Spreads'** investigates the role of frictions in credit derivatives and their effects on the underlying securities. My co-author Yalin Gunduz and I use a liquidity shock that affects the market for credit default swaps (CDS) and study whether and how it propagates to the underlying market for bonds. While recent work on the CDS market has focused on the effect of limited capital investment or dealer failure on trading conditions and liquidity (for example, Siriwardane (2019) or Eisfeldt et al. (2018)), we use a liquidity shock driven by the exit of a large dealer in order to study the effects of CDS derivatives on the bond market.

By combining unique data on CDS transactions and investor security holdings available at the Deutsche Bundesbank, we identify investors that trade both CDSs and bonds on the same reference entity. We then document that following the exit of the dealer, these investors pay higher prices for CDS protection and they trade less CDSs. Interestingly, they also decrease their holdings of the underlying bonds. We also document an economically significant effect on bond yields: the yields of bonds issued by CDS-traded firms for which the exiting dealer intermediated relatively more CDSs increase. The effects are strongest the riskiest the underlying firm. Overall, our results suggest that CDSs and bonds are complementary: CDSs complete markets and as such they can improve the improve the bond market by increasing investor demand and reducing credit spreads. In other words, frictions in the CDS market can hurt bond markets, raise credit spreads, and generate negative real effects.

The third essay is titled **'The Value of Bank Privileged Information: Evidence from the CDS Market"**. Jointly with my co-authors Steven Ongena and Cosimo Pancaro we study how information is valued and transmitted in OTC markets. To do so, we investigate the trading terms of banks buying default protection in CDS markets. As banks are likely informed investors (Fama 1985; James 1987), it is conceivable that they have to pay a 'lemons premium' when buying credit default protection on their own customers. However, it can also be conceived that banks might enjoy a discount when trading in the CDS markets. If trades with banks disclose private information, market makers could then monetize this information when trading with other investors.

We address this research question by relying on the universe of Euro-wide CDS transactions collected by the European Central Bank under the European Markets Infrastructure Regulation (EMIR). These data permit to compare the trading terms that market makers offer to banks and to non-bank investors for equal contracts.

Our findings reveal that banks are able to trade at a discount. Bank trades are valuable for CDS dealers, the latter being willing to compensate banks for their business. Subsequently to trading with a bank, dealers stand to gain from trading with non-bank investors on the same reference obligation. These findings suggest that banks might indeed hold private information which they are willing to share with OTC market dealers in exchange for competitive access to derivatives. Overall, the project allows us to better understand the role of information in OTC markets and it suggests that bank private information could improve securities markets, when dealers act as a carrier for price discovery.

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Capital Inflows and Skill (Mis)allocation*

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Abstract

This paper investigates whether abundant capital inflows can negatively affect the allocative efficiency of human capital in the presence of financial frictions. To address this question, we exploit exogenous variations in banks' ability to channel capital inflows in Portugal over the 2002-2007 period, coupled with both bank-firm exposures and panel data at the worker level. Firms in a relationship with a bank that channels capital inflows rely more on external debt, increase their skill intensity, and pay higher wages. The effects are larger in the less productive sectors. Our results suggest that skills might concentrate in the less productive firms and sectors in periods of abundant capital inflows, potentially dampening long-run productivity growth.

Keywords: Capital flows, Credit Supply, Labor, Skills, Talent Allocation

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1 Introduction

There is a large debate on whether or not countries benefit from large capital inflows, and to which extent. In the absence of mature financial institutions that can efficiently channel funds, international capital inflows might lead to a misallocation of the country's resources. One of the most important factors of growth is human capital. Do large capital inflows affect the allocation of workers and skills? If yes, how? Can massive capital inflows lead to a decline in the allocative efficiency of human capital? Answering these questions is all the more important as changes in the allocation of skilled workers might have persistent effects: labor flows are relatively rigid, and workers accumulate firm- and industry-specific human capital on the job.[1]

The literature has shown that in the presence of financial frictions, abundant capital inflows can lead to a decline in the allocative efficiency of capital (Gopinath et al. 2017). There is little empirical evidence, however, on whether capital inflows also affect the allocation of labor and skills. One reason is that understanding the extent of labor and skill misallocation from firm-level data is challenging. If both workers and capital concentrate in the less productive sectors, the marginal productivity of labor might not reflect the decrease in its allocative efficiency. The higher ratio of capital per worker - as well as the increase in skill intensity - might partly offset the effects of the lower total factor productivity.[2] Therefore, measuring the effects of capital inflows on the allocation of workers requires not only firm level data, with exogenous sources of variation in firms' exposure to capital inflows, but also panel data at the worker level. This panel data, coupled with information on workers' level of education and occupation, will allow us to track workers, and more specifically skilled workers, across firms and sectors over their career.

This paper exploits exogenous shocks to firms' access to capital inflows coupled

[1]Hoffman et al. (2019) provide evidence on how the accumulation of industry-specific human capital can dampen workers' future mobility.

[2]If we consider a Cobb-Douglas production function $f(K, L) = aL^{\beta}K^{\alpha}$, we observe that $\frac{\delta f(K,L)}{\delta L} = \frac{\beta K^{\alpha} a}{L^{1-\beta}}$. The higher skill intensity proxied by β, as well as the higher amount of capital K might offset the effects of a lower a on the marginal productivity of labor.

with census data from Portugal to show that the capital inflows triggered by the introduction of the euro lead to a change in the allocation of workers and skills. Skilled workers are more likely to join firms more exposed to capital flows, even if these firms are less productive. The effects are stronger in the non-tradable sectors, which is initially less productive, and where productivity has decreased over the period. Overall, credit, employment and skill intensity increase in the less productive non-tradable sector in periods of large capital inflows.

The exogenous variations in firms' access to capital inflows stem from the adoption of new accounting norms in Portugal in 2005 that heterogeneously affect banks' capacity to channel these fund flows. Portuguese banks are central to the transmission of international funds to the Portuguese economy, accounting for approximately half of the €165 billion Portuguese foreign debt (Chen et al. 2012; Reis 2013). The new accounting norms we consider - the International Accounting Standard Nineteen (IAS 19) - heterogeneously affect bank capacity to channel capital inflows through their exposure to their defined benefit (DB) plans. In a DB plan, the bank pledges retirement benefits to their employees.[3] IAS 19 increases the accounting value of the DB plan liabilities, leading banks to make cash contributions to their pensions funds, which subsequently decreases their capitalization.[4][5] In 2005, the total contributions of banks to their DB plans hence amount to 2.5 billion euros, or 21% of their equity capital. However, under Basel 1, coporate loans require at least 8% of capital. Because raising equity is costly for banks, affected banks subsequently reduce lending - and borrowing from international markets - and firms in a relationship with affected banks have a lower access to capital inflows.

We exploit the introduction of IAS 19 as a natural experiment to address our research question for the following reasons. First, the effects on bank capacity to

[3] The accounting value of the liabilities of a DB plan is the net present value of these benefits. To arrive at this value, the regulator defines 'actuarial' assumptions on the discount rate, the retirement age, the expected wage growth of beneficiaries as well as their life expectancy.

[4] The introduction of IAS 19 leads to a 35% increase in the accounting value of DB plan liabilities through the inclusion of new benefits to DB plans and a change in the 'actuarial assumptions' used to value the liabilities

[5] In another context, Rauh (2006) exploits firm mandatory contributions to their pension funds as an exogenous shock to internal financial resources and investigates the effect on firm investment.

channel capital inflows are both heterogeneous across banks and exogenous to bank characteristics, as ex-ante banks' exposure to DB plans varies mostly for institutional reasons. Portuguese banks have DB plans of heterogeneous size, ranging from 0% to more than 100% of their common equity. Second, the introduction of IAS 19 is not related to any changes in macroeconomic or financial conditions, as the changes are triggered only by the adoption of international accounting standards. Third, the introduction of IAS 19 does not affect firms and their demand for credit, as employees from non-financial firms are covered by the national security system (NSS).[6] Fourth, the effects on bank internal resources and firm's access to capital inflows is large. Finally, the effects of the introduction of IAS 19 are not anticipated in magnitude and coverage, as the conditions of the implementation of IAS19 in Portugal are only determined in 2005, the year of the shock.

Our analysis follows two steps. In a first step, we show that banks with a low exposure to DB plans, where employees are mostly covered by the NSS, *NSS banks*, have largely channeled capital inflows after the shock compared to *DB banks*, leading to an increase in leverage for firms in a relationship with these NSS banks. We exploit the Portuguese credit register, which covers the credit exposures of all banks and firms in Portugal, and we combine it with data from bank, firm and DB plan financial statements. We find that, on average, loan growth is 18 percentage points higher in NSS banks relatively to DB banks after the introduction of IAS19. Our favorite specification includes a wide range of bank balance sheet characteristics as well as firm fixed effects to control for firm demand for credit (Khwaja and Mian 2008). We then show that firms exposed to bank-channeled capital inflows, or in a relationship with NSS banks, increase leverage relatively to the control group of firms in a relationship with DB banks *only* after the shock. While prior to the shock, treated and control firms face similar trends, treated firms experience a relative increase of 8 pp in loan growth following the introduction of IAS19. These results are robust to different measures of treatment intensity, to the inclusion of 52 industry fixed effects, of a large set of firm and bank controls, and are stronger for small firms.

[6]Except the telecommunication sector. Resutls are robust when we exclude it

In a second step, we investigate whether firms exposed to bank-channeled capital inflows increase employment and their share of skilled workers. To do so, we match the bank-firm dataset with a census of all Portuguese employees in private sector firms. The census includes detailed information on each employee's career, level of education, occupation and earnings. We identify workers' skills using the detailed census information on both their level of education and the skill-intensity of their occupation. Portugal, in the 2000s, has the largest share of adults without upper secondary education among OECD countries, with an average level of education of 7 years, potentially creating a skill shortage.

Our first finding is that both employment and the share of skilled workers - defined either as workers with at least secondary education or in skill-intensive occupations - increase more in firms exposed to bank-channeled capital inflows. We estimate a difference-in-differences specification at the firm level where the dependent variable is the growth of employment across four categories of education and five occupations. In these specifications, we control for a large set of firm characteristics and for industry fixed effects. We find that the 8 pp relative increase in loan growth leads to an increase of 3.6 pp in the employment growth of high-skilled workers. Thus, we document an elasticity of skilled employment to credit supply of 45%, while the corresponding elasticities for high school-, middle school- and elementary school-educated workers are equal to 26%, 22% and 15%.

Our second result is that the relative increase in the employment of high-skilled workers in firms exposed to bank-channeled capital flows results from skilled workers switching away from firms in a relationship with DB banks. We estimate a linear probability model at worker level where we control for worker characteristics and firm fixed effects. We show that high-skilled workers are more likely to join firms exposed to bank-channelled capital inflows and to leave control firms.

Our third result is that capital and workers concentrate mostly in the non-tradable sector when firms are exposed to capital inflows. In 2002, the non-tradable sector is less productive than the tradable sector in Portugal, and most importantly, markups and productivity have decreased in this sector over the period, and more so than in the rest of the EU and for the main trading partners. Among firms that are exposed to capital inflows, we find that skill intensity has increased mostly in the non-tradable sector, at the expense of the tradable one.

To shed light on the reasons for these flows of skilled workers, we estimate a triple difference-in-differences model explaining wage changes for switchers. The granularity of the data allows us to include worker fixed effects, and thus ensure that unobservable worker characteristics do not bias the estimates. After 2005, college and high-school educated workers experience a 2.4% and, respectively, 2.7% higher increase in wages when joining firms exposed to capital flows. These findings are consistent with the talent drain hypothesis: educated workers switch to benefit from better opportunities in firms that benefit from capital inflows. Overall, these results suggest that skilled workers have followed capital inflows, potentially leading to a misallocation of skills.

Our paper first contributes to the growing literature on credit supply expansion and misallocation. Pioneered by Restuccia and Rogerson (2008) and Hsieh and Klenow (2009), the misallocation literature documents large differences in the efficiency of factor allocation across countries. Dias et al. (2016) and Garcia-Santana and Ramos (2015) document a sharp decline in allocative efficiency during periods of large capital inflows in Portugal, and Spain, respectively.[7] We provide the first empirical evidence that capital misallocation can lead to changes not only in labor allocation (Mian et al. 2019; Borio et al. 2016) but also in the allocation of skills across sectors, with the skill intensity increasing in less productive sectors.

Our paper also contributes to the literature that investigates the driver of the allocation of talent. Murphy et al. (1991) consider the effects of returns to talent. Another strand of the literature documents a complementarity between skills and capital. Bai et al. (2018) show that the banking deregulation in the US has lead to both capital and labor reallocation.[8] In subsequent work, Fonseca and Van Doornik (2019) show that skill intensity and capital expenditures increase jointly at credit-constrained firms in Brazil after 2005.

[7]Reis (2013) Gopinath et al. (2017) and Asriyan et al. (2019) show theoretically how financial frictions can generate capital misallocations in periods of capital inflows.

[8]Baghai et al. (2018) find that the pool of talented workers significantly deteriorates when firms are close to bankruptcy, and Brown and Matsa (2016) that talented workers tend to apply less to firms in financial distress.

Our paper also adds to the abundant literature on the real effects of financial frictions and bank funding shocks. The literature shows an effect on lending (Paravisini 2008; Ivashina and Scharfstein 2010; Chava and Purnanandam 2011; Puri et al. 2011; Berg 2018; Jiménez et al. 2017), firm investment, and employment (Benmelech et al. 2017; Bentolila et al. 2017; Berton et al. 2018; Acharya et al. 2018; Chodorow-Reich 2014; Popov and Rocholl 2018; Berg 2018; Hochfellner et al. 2015; Caggese et al. 2017; Siemer 2014). We contribute to this literature in two ways. First, we are able to precisely quantify how a decrease in bank internal resources translates into a decrease in credit growth, as we focus on a funding shock triggered by a change in accounting norms that is orthogonal to both bank and firm health. This change is due to the harmonization of accounting standards across countries, and not to changing macroeconomic, financial, or fiscal conditions that could simultaneously induce economic distress on banks and firms. Second, we identify the effects of the bank funding shock on the allocation of skills in the economy in a period of large capital inflows. While Berton et al. (2018) document that, in bad times, low-skilled workers are more affected by bank funding shocks, with implications on inequality, we show that in good times, bank financial health affects the allocation of skilled workers in the economy.

Finally, our paper also contributes to the recent literature that investigates the real effects of accounting changes. The wide adoptions of international standards such as the IFRS or GAAP were found to have some direct and positive real effects on non-financial firms, mainly because they increased managerial effort. There is recent evidence of improvements in market liquidity (Armstrong et al. 2010) as well as reductions in firm cost of debt (Daske et al. 2008, 2013; Florou and Kosi 2015) and increased investment (Shroff 2017). However, when the changes in accounting norms affect the internal resources and capital buffer of banks, they might have negative effects on the real economy. Dou et al. (2018) show that banks cut mortgage credit following the introduction of FAS 166 and FAS 167, which required them to consolidate off balance sheet assets. We document the spillovers to the real economy of changes in the accounting norms for banks.

The rest of the paper is organized as follows. Section 2 describes the economic background and the data. Section 3 presents the identification strategy and the institutional background of bank DB plans in Portugal, the IAS 19 accounting reform, and its effect on bank resources. Section 4 and Section 5 provide the results on credit and skill allocation, respectively. Section 6 concludes.

2 Background and Data

2.1 Capital Inflows and Capital Misallocation in Portugal, 2000 - 2010

While the financial integration of the Eurozone was supposed to boost economic growth by facilitating risk sharing across countries, decreasing interest rates and improving resource allocation efficiency, it has not necessarily translated into higher growth for Southern European countries. Hence, Portugal, but also Spain, experience stagnant or declining productivity after the Euro integration, as Figure 1 illustrates.[9]

INCLUDE FIGURE 1

The decrease in productivity in Portugal over the 2000-2010 period is accompanied by growing capital inflows, as Panel B of Figure 1 illustrates. Portugal owes foreigners €165 billion in 2007, an amount approximately equal to the whole of its GDP for that year, while in the mid-1990s, Portugal's net foreign debt is close to zero (Reis 2013). As in Portugal the main source of external funds are banks, Portuguese banks play a key role in the transmission of these capital flows, serving as the intermediary between the foreigners and Portuguese firms and households. Chen et al. (2012) estimate that in 2007, banks account for approximately half of the Portuguese foreign debt. Categorizing gross capital flows into equity, foreign

[9] While in 2000 Portugal is a rich country by world standards - but the poorest of the 12 countries that initially formed the euro area - real GDP per capita has grown by only 0.6 percent per year over the 2000-2007 period. Consumption grew faster than output during this period, and real wage increased in spite of rising unemployment. The unemployment rate in 2007 was 8.9 percent, the highest it had been since 1960 with the exception of 1985, and almost half of that unemployment rate was generated between 2000 and 2007 (Reis 2013).

direct investment, and bank debt, Lane (2013) estimates that between 2003 and 2007, bank debt account for 68 percent of these flows.

Negative productivity growth implies that a given amount of capital and labor produce less output over time. While increasing productivity is often related to innovation and learning, negative productivity growth does not necessarily reflect "forgetting" (Cette et al. 2016). It might rather result from a less efficient allocation of resources across firms over time, thereby reducing the average efficiency of the economy.

Did the decrease in real interest rates during the financial integration lead to a worsening in the allocation of capital? Such an effect could arise through two non-exclusive channels. First, international macroeconomics has long pointed out the risk that capital inflows boost non-tradable output such as services or construction, which tend to have lower productivity (and productivity growth) than manufacturing and other tradable (Kalantzis 2014; Benigno et al. 2015). A second channel includes misallocation of capital across firms within sectors following fast credit growth (Reis 2013; Gopinath et al. 2017). Gopinath et al. (2017) show that the marginal product of capital has become more dispersed in Southern Europe within manufacturing, including in Portugal. Dias et al. (2016) find that within-industry misallocation almost doubled between 1996 and 2011 in Portugal. Similar patterns for other European countries regarding higher levels of misallocation in the service sector and/or increasing levels of misallocation over the sample period were also recently documented in other countries (see Beņkovskis (2015) for Latvia and Calligaris et al. (2016) for Italy).

One reason why capital might have been misallocated relies on financial market imperfections/financial market deepening. Reis (2013) and Gopinath et al. (2017) argue that the weakness of Portugal's financial sector caused the capital inflows to be largely misallocated to firms with a high net worth or collateral. A growing theoretical literature models a decrease in the information screening of loans in period of large inflows (Asriyan et al. 2019). Our identification allows us to identify the role of private credit in the misallocation of capital inflows and the effects on the allocation of labor.

2.2 Data Sources

Our empirical analysis relies on three databases that we merge using unique firm and bank identifiers: the Portuguese credit register, bank financial data, and the Portuguese census.

2.2.1 Bank-firm Exposures: The Portuguese Credit Register

We obtain bank-firm credit exposures from the Portuguese credit register. The credit register is held by the Bank of Portugal and covers *all bank loans* above 50 euros granted to firms from 1980 to present. For each month and bank-firm exposure, the credit register provides information on both the lenders' and the borrowers' identities, as well as on the amount of credit that is outstanding, along with borrowers' repayment position.

We also extract the credit history of each firm from the credit register by tracking their records back to 1995. With this, we build four variables that provide information on the firm credit history: (1) the average loan size of the firm over the previous 10 years - or since the firm start date -, (2) the number of months with positive credit exposures, (3) an indicator for whether the firm is in default at the time of the analysis, and (4) an indicator for whether it had any history of defaults.

2.2.2 Bank Level Data

We collect bank-level data from two different databases of the Bank of Portugal. We first use the Bank's Monetary and Financial Statistics that contain monthly information on bank balance sheets. We match these data with a second database with yearly information on bank DB plans. Bank balance sheet data is at the bank level and available for the 59 Portuguese banks in 2004, while bank DB plan data is at the banking group level, covering the 13 Portuguese banking groups that sponsored employee pension plans over the period of analysis. Bank DB plan data include the total assets and liabilities of each DB plan, the disaggregated actuarial variations, the pension expenses, as well as the cash contributions of the sponsor bank to the DB plan.

2.2.3 Employee-level Data: Quadros de Pessoal

To investigate the effects of the capital inflows on the allocation of skills in the Portugese economy, we use the Quadros de Pessoal database, a census of all private sector firms in Portugal that employ at least one worker. The census is conducted each October by the Portuguese Ministry of Employment and provides detailed information on the workforce of each firm. In addition, each firm and each worker entering the database are assigned a unique time-invariant identifying number that allows us to follow firms and workers over time. Over the 2004-2006 sample period, the available information covers 350,000 firms and the complete career history of 3 million workers.

The Portuguese census asks employers to report each employee's social and demographic characteristics, employment start and end dates, as well as an extensive set of job characteristics, such as the type of employment, job title, wage and hours worked per year.[10] Socio-demographic characteristics include years of experience, level of education, year of last promotion, age, gender and nationality.

We use two variables to measure workers skills: the worker level of education and the type of occupation. We first group workers into four levels of education: up to elementary education, middle school education, high school education and college education.[11] Second, we follow Caliendo et al. (2017) and Mion and Opromolla (2014) and group workers into five occupations based on the worker classification available in the Quadros de Pessoal. In the matched employer-employee data set, each worker, in each year, has to be assigned to a category following a compulsory classification of workers defined by the Portuguese law (Decreto Lei 121/78 of July 2nd 1978). The classification is based on the tasks performed and the skill requirements, and each category can be considered as a level in a hierarchy defined in terms of increasing responsibility and task complexity. On the basis of this hierarchical classification, we partition the available categories into the following five occupations. We assign "Top executives (top man-

[10]The information on earnings includes the base wage (gross pay for normal hours of work), seniority-indexed components of pay, other regularly paid components, overtime work, and irregularly paid components.

[11]These four levels of education correspond to 6, 9, 12, and 16 years of education.

agement)"; "Intermediary executives (middle management)"; "Supervisors, team leaders" to *Managers*; "Higher-skilled professionals" to *High-skilled Operational Occupations*, "Skilled professionals" to *Skilled Operational Occupations*; "Semi-skilled professionals" to *Semi-skilled Operational Occupations*, and the remaining category "Non-skilled professionals" to *Non-skilled Occupations*.

Finally, in addition to worker characteristics, the Portuguese census database also includes key firm level data such as total sales, starting capital, year of creation, number of employees, the legal and ownership structures of the firms, 5 digit industry identification numbers as well as parish and county information.

2.3 Sample Construction

We build our sample for the main empirical analysis the following way. First, we start from the Portuguese Census and keep all the private firms from the non-financial sector of the economy that hired at least one worker in the pre-treatment period. We, therefore, drop financial firms, state-owned companies and entrepreneurs. We then use the unique firm identifier to match the yearly census information with the data on the credit exposure and history from the credit register. Finally, we use the bank identifier in the credit register to merge this dataset with the bank balance sheet and DB pension plan data.

3 Identification

Our identification strategy relies on the adoption of new accounting norms for the DB plans of Portuguese banks. These new accounting norms resulted in exogenous and heterogeneous changes in banks' ability to channel capital inflows. This section presents institutional detail on bank DB pension plans in Portugal, the effects of the IAS 19 accounting reform on banks and our measure of treatment at the bank and firm levels.

3.1 Bank DB Pension Plans in Portugal: an Overview

While Portuguese workers had been covered by the National Social Security Pension Scheme since the 1970s, Portuguese banks started offering pension plans in the late 1980s, following the adoption of the 1986 Social Security Act.[12] The main reason why banks substituted to the State Pension Scheme was the tax deductibility of DB plan contributions. Only banks and telecommunication firms, however, started offering private DB plans, with banks accounting for up to 80% of all the assets under management. We are, therefore, exploiting an accounting reform that mostly concerned banks, leaving the rest of the economy unaffected.[13] At the end of 2004, bank DB plans cover more than 180,000 employees, or 6% of the working population, and bear liabilities amounting to 9.2 billion euros, or 6% of Portuguese GDP (Autoridade de Supervisao de Seguros e Fundos de Pensoes).[14]

Since the implementation of the first bank DB plans in the late 1980s, there has always been a lot of heterogeneity across banks in their exposures to DB plans. Banks offering private DB plans have always coexisted with banks that do not have pension obligations for their employees, such as small banks - for which the fixed costs of implementing of a DB plan would be too high - and foreign banks. Hence, in 2005, 9 out of 22 Portuguese banking groups covered in our analysis are not offering pension plans. But even across large banks that do sponsor a private DB plan, which account for over 80% of the banking sector assets in 2005, there is a lot of heterogeneity in the size of their DB plans. This is first due to the consolidation of the Portuguese banking sector since the 1990s, with banks making acquisitions of competing banks with or without pension plans. Another reason is that some banks, such as Caixa Geral de Depositos, the largest Portuguese bank, transferred part of their pension plan obligations to the public sector in the beginning of the 2000s.[15]

[12]Decreto-lei 396/86, de 25 de Novembro https://dre.tretas.org/dre/8413/decreto-lei-396-86-de-25-de-novembro

[13]Our specifications include industry fixed effects which relieve some concerns that our results would be driven by the telecommunication industry being also affected by the reforms. Our results are also robust to excluding this sector of the economy.

[14]$http : //www.asf.com.pt/NR/exeres/21E954ED - 7325 - 4CE6 - 8626 - 11AFE2245D5A.htm$

[15]At end 2004, with the publication of Decree Laws nos. $240 - A/2004$ of 29 December

Figure 2 plots bank pension liabilities as a percentage of bank equity in 2004 for the 6 main Portuguese banks. Bank exposure to their pension plan ranges from 19% to 133% of equity, is highly heterogeneous across banks and not correlated with the size of the bank. Table C.1 in the online appendix provides more information on the bank DB plans of the 6 largest Portuguese banks.[16]

INSERT FIGURE 2

3.2 The Introduction of IAS 19

The introduction of IAS 19 on January 1st 2005 resulted in a 35% increase in the accounting value of bank DB plan liabilities. As a result, sponsor banks had to make cash contributions to their DB plans as well as prudential deductions from Tier 1 capital, which affected their capitalization.

The Effects of Bank DB Plan Liabilities

IAS 19 was adopted in 2005 in Portugal in the context of the implementation of the IFRS norms. The objective of IAS 19 was to harmonize the accounting rules for employee pension benefits across countries. While the IFRS norms concerned a large set of accounting standards and affected all major banks and firms in Portugal, IAS 19 was the only IFRS rule that led to direct cash contributions and had such a large impact on the capitalization of banks, as Table C.3 of the online appendix shows.

The adoption of IAS 19 led to a 35% increase in the accounting value of bank DB plan liabilities, from 9.2 up to over 12 billion Euros. The increase in bank DB plan liabilities resulted from two major changes. First, the range of benefits covered by bank pension plans was extended to post-employment medical care and life insurance, which were previously covered by the national security system. This

and $241 - A/2004$ of 30 December, CGD employee retirement and survivors' pensions liabilities for the length of service provided up to 31 December 2000, were transferred to Caixa Geral de Aposentacoes (CGA). The CGD Pension Fund, by way of compensation, transferred the provisions set up to cover the referred to liabilities, to CGA. Liabilities totalled EUR 2,510 million in the beginning of 2004, with EUR 1,434 million of assets having been transferred during the year (CGD Annual Report, 2005).

[16]Data are publicly available in each bank 2004 and 2005 annual reports.

extension accounted for about 50% of the increase in the value of bank DB plan liabilities, as Figure 3 illustrates.

Second, IAS 19 required the revision of the actuarial assumptions used by banks to estimate the accounting value of their DB plan liabilities. In a DB plan, the bank pledges retirement benefits to employees according to a formula that is a function of each employee's age, tenure and salary. Thus, a bank sponsoring a DB plan has a financial liability equal to the present discounted value of the payments pledged to current and future retirees. The calculation of the accounting value of a DB plan liabilities relies on actuarial assumptions, which includes economic assumptions - the discount rate, the wage growth rate and the inflation rate - and demographic assumptions - life expectancy, retirement age and rate of employment termination before retirement. IAS 19 required the harmonization to the international standard of two major actuarial assumptions: the discount rate and the life expectancy. The discount rate used to calculate the present value of bank DB plan liabilities was revised downwards by 50 basis points - from 5.25% to 4.75% - to better match the long maturities of the obligations. The life expectancy of female workers, on the other hand, was revised upwards to account for the longer life expectancy of women, as before the introduction of the IAS19 standards actuaries were using one single life expectancy table for both male and female employees. The decrease in the discount rate and the increase in the life expetancy both accounted for around 25% of the effect, as Figure 3 illustrates.[17]

INSERT FIGURE 3

The Effects on Sponsor Banks' Capitalization

The financial situation of a DB plan can affect the sponsor bank financial flexibility through two channels: the *funding* channel - when the sponsor bank has to make direct cash contributions to the pension fund -, and the *accounting*

[17] Figure X in the online appendix plots the aggregate variations in the bank DB plan assets and liabilities over the years and illustrates the effect adopting IAS 19 on the value of bank pension plan liabilities. Additionally, we provide in Section F in the online appendix extracts from the second largest Portuguese bank 10-K financial and pension plan statements. These illustrate how the accounting value of the liabilities has been affected.

channel - when the sponsor bank has to recognize *actuarial losses*, i.e. losses resulting from changes in actuarial assumptions, in its balance sheet and make prudential deductions from Tier 1 capital.

Following the large and broadly unanticipated increase in the accounting liabilities of bank DB plans triggered by IAS 19, sponsor banks had to make substantial cash contributions to their DB plans. The sponsor of a DB plan is required to make cash contributions to the pension plan to ensure that the DB plan is never "underfunded": i.e. the market value of the plan assets is higher than the present discounted value of the pension liabilities. Figure **??** shows bank cash contributions to their pension plans from 2003 to 2007. The effect of IAS19 is large: direct bank contributions to their pension plans spike in 2005, amounting to 2.35 billion euros, which represents 20% of the equity of affected banks.

Banks also had to make significant deductions from their Tier 1 capital to account for the actuarial losses. A bank can indeed defer the reporting of most of the actuarial losses in the income statements to subsequent years by amortizing these actuarial losses over a period of 10 to 20 years.[18,19] These deferred actuarial losses, however, have to be deducted from Tier 1 capital.[20]

Portuguese banks did not anticipate the magnitude of the effects of IAS 19 on the liabilities of their DB plans and the resulting contributions before 2005 for the following three reasons. First, even if the European Parliament approved the adoption of new accounting standards in July 2002 for an implementation as of January 1st 2005, the exact parameters of the new accounting standards were only defined in 2004. In particular, the conditions of the recognition of actuarial losses were fully defined only in December 2004 by the *Amendment to IAS 19 Employee Benefits: Actuarial Gains and Losses, Group Plans and Disclosures.*

[18]Pension expenses on the income statements are calculated as the sum of the forecasted annual pension commitments - also known as the "service cost" of the plan - the interest cost of the plan and the amortization amounts of the actuarial losses, net of the expected return on the plan's assets.

[19]The share of the actuarial losses that can be deferred and hence not declared as losses in the account statement is defined by the *corridor rule* that we describe in Section B of the online appendix.

[20]Section B in the online appendix provides more detail on the accounting rules of DB plans in Portugal before IAS 19. Figure B.1 illustrates how a 50 million Euros increase in the accounting value of a bank's DB plan liabilities can lead to contributions and prudential deductions.

Second, Bank of Portugal defined the accounting treatment of actuarial losses in Portuguese Banks following IAS 19 only in February 2005 (*Notice 2/2005 of Bank of Portugal*). Third, the possible exemption of some pension liabilities was actively debated until end of 2005. In 2004, CGD pensions liabilities for the length of service provided up to 31 December 2000 are transferred to the National Pension system in part to spare CGD from the IAS 19 shock. Subsequently, in November 2005, Millenium BCP - the largest private Portuguese banking group - proposed that their pension liability be also transferred.[21] While BCP's request was initially rejected, a similar context in 2011 was met with a favourable outcome, as the Portuguese Government did transfer the entire bank pension plans into public ownership as part of the tripartite agreement with the ECB, EC and the IMF. The fact that, during 2005, banks had to make substantially larger pension contributions and prudential deductions than in previous years provides additional evidence that the funding shock was largely unforeseen.

Overall, the richness of this institutional setting allows us to exploit a funding shock that is: 1) heterogeneous across banks, because of the significant ex-ante heterogeneity in the coverage of the pension plans; 2) not related to any changes in macroeconomic or financial conditions as it is triggered only by the harmonization of accounting rules across countries; 3) specific to banks, and only to a sub-sample of these banks, as the private pension system in Portugal does not cover any other sector of the economy except the financial and the telecommunication sectors; 4) of a large magnitude, and in a period of large capital inflows, which allows to identify how banks channel capital inflows and the effects on the allocation of skills; 5) not anticipated in magnitude and coverage, as the conditions of the implementation of IAS19 in Portugal are only determined the year of the shock.

3.3 Identifying Treated Banks and Firms

We first define bank-specific and firm-specific measures of the treatment intensity and then split banks and firms in two groups based on the treatment intensity.

[21]https://www.cmjornal.pt/economia/detalhe/millennium-bcp-propoe-transferencia-de-fundo-de-pensoes

At the bank level, we define the treatment intensity as the bank exposure to its DB plan ex-ante, measured by the ratio of the bank DB plan liabilities to the bank equity in 2004. This ratio captures the magnitude of the shock by scaling the size of the DB plan to bank internal funds as proxied by the bank equity. All our results are robust when using as alternative measures the ratio of the change in pension liabilities due to IAS19 to the bank equity, the ratio of the 2005 cash contribution to the bank equity, and the ratio of pension liabilities to banking assets (see for example Table D.3 in the online appendix).

Figure 2 illustrates the heterogeneity of the bank exposure to their DB plan, and hence the intensity of the treatment, across the 6 largest Portuguese banks.[22] The ratio of DB plan liabilities to bank equity varies from 19% to 133%. The magnitude of the treatment is related neither to the size of the bank, as measured by total assets, nor to its equity ratio. Table 1 confirms that the variable $Treatment\ Intensity_b$ varies significantly across banks in the total sample: the average and the median are at 40%, the 10^{th} percentile 0% and the 90^{th} percentile 104%.

At the firm level, the $Treatment\ Intensity_f$ variable is the weighted average of the treatment intensity of the banks the firm borrows from. It is calculated as follows:

$$Treatment\ Intensity_f = \sum_{b=k} \alpha_{k,f} \times Treatment\ Intensity_k,$$

where

$$\alpha_{b,f} = \frac{Loan_{b,f,2004}}{\sum_{b=k} Loan_{k,f,2004}}.$$

Hence $\alpha_{b,f}$ measures the relative credit exposure of firm f to bank b during the pre-treatment period, i.e. in 2004.

We hence restrict our sample to firms with a positive credit exposure in 2004. As a result, the final sample includes a total of 161,202 firms, 59 banks, 333,788 bank-firm exposures and more than 2 million employees working at these firms in

[22]The data is publicly available in the financial reports of these 6 banks and reported in Table C1 in the online appendix.

2004. Tables 1 and 2 provide summary statistics on banks, firms, and employees in this final sample.

INCLUDE TABLE 1

INCLUDE TABLE 2

Table 1 shows that the variable $Treatment\ Intensity_f$ averages 0.39 and has a standard deviation of 0.28. In the first 10th percentile, there are firms borrowing only from non-affected banks, while the 90th percentile and above captures single-bank firms borrowing from banks treated with high intensity.

The summary statistics in Table 1 also indicate that the median firm in the control group is very similar to the median firm in the treated group along the following characteristics: size, age, credit history and composition of the workforce.

We then split banks and firms in two groups based on the measure of treatment intensity. At the bank level, the variable $Treatment\ Dummy_b$ takes the value one for banks with a treatment intensity above the median, i.e. with a ratio of DB plan liability to equity above 40%. At the firm level, the variable $Treatment\ Dummy_{firm}$ indicates firms for which more than half of their pre-period credit exposures originated from banks treated with high intensity. The assignment leads to 13 treated banks and 46 control banks, associated with 80,846 treated firms and 80,356 control firms. In the rest of the paper, we identify "treated" banks or firms when their $Treatment\ Dummy$ equals 1.

4 Credit Allocation

We exploit the introduction of IAS19 in 2005 as a shock to bank capitalization and ability to channel international capital flows. We first investigate the effects of the shock on bank credit expansion looking at differences in the growth rate of bank-firm credit exposures. Second, we test whether firms that are still exposed to capital inflows after the shock, i.e. firms that are not in a relationship with a DB-plan bank, increased leverage.

4.1 Bank Credit Expansion

4.1.1 Main Result

To estimate the effects of IAS19 on bank capacity to channel capital inflows and to test the parallel trend assumption, we first plot the growth in corporate lending by treated banks and control banks over the 2004 to 2007 period.

INCLUDE FIGURE 4

Figure 4 shows that the growth in lending by treated banks slows down relatively to the growth in lending by control banks from mid-2005, while it followed a parallel trend from 2003 to 2005. The two lines represent the percentage growth in credit since 2004 on a monthly basis. The lag of six months we observe before the effect kicks in is consistent with banks only having to report the financial situation of their DB plan at the end of the year, and with the fact that the institutional details of the implementation of IAS 19 were only fully defined in the first semester of 2005. In addition, part of the bank-firm exposures come from revolving lines of credit, which are negotiated ex-ante for a given period of time.

We further investigate the effects of the funding shock on bank credit expansion in a difference-in-differences model at the bank-firm level where the dependent variable is the growth rate of the bank-firm credit exposures.

To build the dependent variable, the growth rate of the bank-firm credit exposures from 2004 to 2005-2006, we first construct a balanced panel of monthly bank-firm exposures that covers the 2004-2006 period by aggregating all outstanding loans at the bank-firm level and filling all months for which a pair is missing with a zero exposure. Hence, if bank b lends to firm f and the loan is repaid after a year, the bf pair will be in our data during the entire sample period, even though the bank-firm exposure will be equal to zero for two out of the three years of the analysis.[23]. We then follow Bertrand et al. (2004) and collapse our monthly panel of bank-firm exposures in two sub-periods, 2004 and 2005-2006, by taking the average. Finally, we compute the growth rate in each bank-firm exposure using

[23]For the purpose of our analysis, we exclude loans granted by non financial and monetary institutions, which account for less than 5 per cent of total credit in Portugal.

the Davis and Haltiwanger (1992) growth measure

$$Credit\ Growth_{b,f} = \frac{Credit_{b,f,post} - Credit_{b,f,pre}}{\frac{1}{2}(Credit_{b,f,pre} + Credit_{b,f,post})},$$

where $Credit_{b,f}$ is the exposure of bank b to firm f. In addition to easing the interpretation and comparability of the estimates, this growth rate has good statistical properties as it is symmetric around zero, bounded in the range $[-2;2]$, and it can accommodate both entry and exit.[24]

We estimate the effect of the funding shock on bank exposure to firms using the following specification

$$\begin{aligned} Credit\ Growth_{b,f} = {} & Firm_f + \beta DBPlan\ Exposure_b + \\ & + \gamma BankControls_b + e_{b,f}, \end{aligned} \tag{1}$$

where $DBPlan\ Exposure_b$ is either our treatment dummy or the treatment intensity variable at the bank level depending on the specification. We cluster standard errors at the banking group × industry levels.[25]

INCLUDE TABLE 4

Column 1 in Table 4 confirms the aggregate result of Figure 4: the growth of bank exposures to firms is 17 percentage points higher for banks that are not affected by IAS19. Non-affected banks have therefore kept expanding credit after 2005. While we observe from Figure 4 that the parallel trend assumption holds between control and treated banks, we include a large set of bank characteristics to further ensure that any differences across control and treated banks do not drive differences in growth rates. The vector $BankControls_b$ includes the logarithm of assets, the capital ratio, a measure of liquidity - assets maturing within one year to total assets -, the ratio of bonds outstanding to assets, loans-to-assets, short

[24]For a thorough explanation of the statistical advantages of using this growth measure, please refer to the technical annex in Davis and Haltiwanger (1992).

[25]Table D.1 in the online appendix shows that results are robust to clustering at the banking group level (22 clusters). In our main analysis, however, we cluster at banking group × industry levels to account for possible correlation in the firm-level residuals induced by including industry fixed effects (Petersen 2009). This also ensures that we have a sufficiently high number of clusters (Cameron and Miller 2015)

term liabilities to assets and the ratio of non-performing loans to total lending, all calculated in the pre-treatment period, i.e., in 2004. Similarly, $Firm_f$ is a vector of firm controls that includes the four measures of firm credit history, the logarithm of total sales, firm age, product per worker and workforce tenure, as well as indicators for legal organization and ownership structure.

Column 2 controls further for firm demand for credit by including firm fixed effects (Khwaja and Mian 2008). We, therefore, compare the supply of credit of a treated bank to the supply of credit of a control bank *to the same firm*. The point estimate of β suggests that, for a given firm, the growth rate of its exposure to a treated bank is also 17 percentage points lower than the growth rate of its exposure to a control bank.

Column 4 suggests that the result also holds also in a specification using the treatment intensity, instead of the treatment dummy, as independent variable: banks with larger pension liabilities relative to their equity tend to increase less their credit exposure to firms after the introduction of IAS 19.

Column 5 shows that the magnitude of the effect is still large and highly significant when we restrict the sample only to banks sponsoring DB plans. This specification provides additional robustness for the possibility of non-random firm-bank matching, which may occur if firms dealing with banks that sponsor pension plans are systematically different from firms dealing with banks without any pension obligation. With this specification, we show that the effect is not driven by including the latter type of banks, which tend to be smaller banks, more local, and possibly more relationship-based.

In Columns 6 and 7, we show that the funding shock also has an effect on the "extensive margin" of lending: the coefficients in columns 6 (negative) and 7 (positive) suggest that treated banks are, respectively, less likely to start new relationships with firms, and more likely to end existing relationships with firms. To obtain this result, we build two new variables. First, we measure new lending with a dummy that equals one if a new loan is granted in the post-treatment period to a firm that has a zero-exposure to this bank in the pre-treatment period. Second, a dummy variable that is equal to one when a credit exposure that is positive in the pre-period becomes zero in the post treatment period. We then estimate equation (1) in a Logit model with these two variables as dependant variables.

4.1.2 Robustness Tests

Tables D.1, D.2 and D.3 in the Online Appendix include a series of robustness tests. First, Column 1 in Table D.1 offers a sensitivity analysis to bank capital buffers. The coefficient on the interaction term suggests that treated banks with lower capital buffers tend to cut lending more than highly capitalized banks. This is another way to measure the treatment intensity. While in all specifications in Table 4, standard errors are clustered at the banking group $\times$ industry levels, Columns 2 to 4 show that results are robust to clustering standard errors at the banking group level only. Finally, Columns 5 to 7 show that the results are robust to restricting the sample to the six main banks in Portugal. These banks jointly account for 87% of the banking assets in Portugal in 2004. Focusing on them eliminates potential noise in the estimates from including smaller institutions. In addition, these six main banks homogeneously implemented the complete set of IFRS rules in 2005.

Table D.2 and D.3 in the Online Appendix show that the results are robust to various definitions of the dependent variables and the treatment variables. In Table D.2, we replicate the main specifications using the delta log as dependant variable instead of our credit growth measure, as in the existing literature. One limit of using the delta log is that it puts more weight on very small loans whose size can easily be multiplied. This accounts for the larger coefficient we observe with this specification. In Table D.3, we define the treatment intensity variable as the *change* in bank pension liabilities to bank equity.

4.2 Firm Borrowing

We now investigate how the changes in bank credit expansion trigerred by IAS 19 has affected borrowing by Portuguese firms.

4.2.1 Main Result

Figure 5 shows that the growth in borrowing has slowed down in firms in a relationship with a DB-plan bank (only) after 2005 compared to other firms. Alternatively, the graph shows that borrowing has accelerated in firms that are still exposed to capital flows (only) after 2005. Before 2005, treated and control firms face parallel trends in credit growth, which suggests that the treatment is exogenous to firm unobservable characteristics.

The figure plots the dynamics of the coefficient β in the following panel model where the dependant variable is the yearly growth rate in the credit exposure at the firm level and the variable *Treated* indicates firms in a relationship with a DB-plan bank

$$
\begin{aligned}
\%Growth\ in\ Credit_{f,y} = {} & \beta_y Treated_f + \\
& + \eta YearFE + \gamma_{y,f} FirmControls + e_{f,y}
\end{aligned}
$$

.

The controls include the firm characteristics and 52 industry fixed effects. To obtain the growth rate in credit at the firm level, we sum the loan exposures of each firm across all banks.

We then collapse our sample into the pre-treatment period (year 2004) and the post treatment period (years 2005 - 2006) by taking the average of the firm monthly exposures to credit over each sub period. We estimate the following specification:

$$
\begin{aligned}
\%Growth\ in\ Credit_{f,post-pre} = {} & \beta \mathbb{1}_{Exposure\ to\ Capital\ Flows_f} + \\
& + \gamma FirmControls_f + e_f
\end{aligned}
\tag{2}
$$

where $\%Growth\ in\ Credit_{f,post-pre}$ is the change in the total credit exposure of firm f between the pre and post-period using again the Davis and Haltiwanger (1992) growth measure. $\mathbb{1}_{Exposure\ to\ Capital\ Flows}$ is a variable indicating whether the firm is still exposed to capital flows after 2005. Alternatively, the dummy takes the value 0 for firms in a relationship with a DB-plan bank. Because we identify firms in a relationship with a DB-plan bank based on bank-firm exposures in the pre-treatment period, we restrict the sample to the 161,202 firms that have total non-zero credit exposures in the pre-period. Firm controls include 52 industry fixed effects, our measures of credit history, the logarithm of total sales, firm age, product per worker and workforce tenure, as well as indicators for legal organization and ownership structure, and bank characteristics, i.e. the logarithm of assets, capital ratios, liquidity ratios, loan-to-asset ratios, short term liabilities to assets, bond funding to assets, and non performing loan ratios in 2004 - weighted by each bank's credit exposure in a firm's total credit in the same year. Standard errors are clustered at the firm main banking group $\times$ industry levels.

INCLUDE FIGURE 5

Table 5 reports the results. The coefficient of $\mathbb{1}_{Exposure\ to\ Capital\ Flows}$ in Column 1 suggests that firms exposed to capital flows increased borrowing more than firms in a relaitonship with DB-plan banks. We find that credit growth is 8 percentage points higher for firms still exposed to capital flows.

Column 2 shows that this result is robust to including our large set of firm controls, which further alleviates the concern that differences between DB-plan banks and control firms might drive our results. The coefficient of $\mathbb{1}_{Exposure\ to\ Capital\ Flows}$ remains stable.

INCLUDE TABLE 5

Columns 5 to 7 confirm that the result holds when we use the intensity of the exposure to capital flows instead of the dummy as dependent variable. Consistently, firm borrowing increases when exposure to capital flows increases.

4.2.2 Heterogeneity of the Effects

This section explores how exposure to capital flows affects borrowing heterogeneously across industries and firm characteristics.

We split our sample into quartiles of productivity, age and size and estimate equation (2) within each sample. Columns 5 to 7 display the results. The effects of the credit expansion seem to be larger in less productive, small and older firms.

In columns 8 and 9, we estimate equation (2) in two sectors: whole sale trade and manufacturing. The non-productive wholesale sector benefited the most from the credit expansion relative to manufacturing. The growth in credit has therefore been lower in the tradable productive sector.

These results are consistent with the growing literature documenting a misallocation of capital flows to the non-tradable sectors and less productive firms (Oberfield (2013), Sandleris and Wright (2014), Dias et al. (2016) and Garcia-Santana and Ramos (2015) document a sharp decline in allocative efficiency during periods of large capital inflows in Chile, Argentina, Portugal, and Spain, respectively).

5 Skill Allocation

In this section, we investigate the effects of the capital inflows on the allocation of not only workers but also skills.[26]

Most skilled workers typically organize production by others and spread their ability advantage over a larger scale (Murphy et al. 1991). In the productive sectore, they will innovate and foster technological progress, hence improving productivity. In the non-tradable sector, their is less room for productivity improvement. The allocation of skilled workers across sectors is therefore key for productivity growth.

What drives the attractiveness of an occupation, sector or firm to skill workers? First, skilled workers might want to spread their higher ability in large and growing markets. Second, compensation contract matters. In an economy where household demand and the price of non tradable good increase, firms in the non-tradable sector might be able to pay higher wages as they expand thanks to credit expansion.

In Portugal, in the 2000s, the supply of skilled workers is low, and hence competition for talent through wages might play an important role in the allocation of workers. In 2004, only 20% of the 25-64 years-old had completed secondary education in Portugal, compared with an average of 60% in OECD countries. The share of the working population with a tertiary education is only 10% (OECD, 2005).

[26] We hence complement the findings of Mian et al. (2019) on credit expansion and the allocation of workers across the tradable and non-tradable sectors.

The educational distribution of the workforce in the 2000s is close to the one in the United States in 1930 (Alves et al. 2010; Goldin and Katz 2009). Probably because of this short supply of educated workers, the returns to college education are the highest in the EU in 2002 (Portugal and de Campos 2004).

5.1 Skill Composition of the Labor Force

We first show that the capital inflows have affected the allocation of workers.

To do so, we collapse our sample into two sub-periods, the pre-treatment - 2004 - and the post treatment periods - 2005 and 2006 -, taking the average number of employees at the firm level over each sub-period. We then estimate the following model:

$$\begin{aligned} Employment\ Growth_f = {} & \beta \mathbb{1}_{Exposure\ to\ Capital\ Flows_f} + \mu Industry_s \\ & + \gamma FirmControls_f + e_f \end{aligned} \tag{3}$$

where $Employment\ Growth_f$ is the change in the total number of employees of firm f between the pre and post-period using the Davis and Haltiwanger (1992) growth measure and $\mathbb{1}_{Exposure\ to\ Capital\ Flows}$ is a variable indicating whether the firm is still exposed to capital flows after 2005 - and therefore takes the value 0 if the firm is exposed to DB-plan bank. $Industry_s$ is a vector of 52 industry dummies and $Controls_f$ is a vector of firm characteristics measured in the year 2004. As previously, firm characteristics include our four measures of credit history, the logarithm of total sales, the logarithm of the number of employees, firm age, product per worker and workforce tenure, as well as indicator variables for the legal organization of the firm and the ownership type - private, public or foreign.

INCLUDE TABLE 7

The coefficient estimate of $\mathbb{1}_{Exposure\ to\ Capital\ Flows}$ in Column 1 of Table 7 suggests that the 8 percentage points higher credit growth that firms exposed to capital flows experienced translated into a 1.7 percentage point higher employment growth. Hence, on average, the credit expansion has translated into a higher employment growth. The elasticity of employment to credit supply we measure is

22%. We have shown previously that capital flows have been allocated mostly to the non tradable sectors, where employees might have followed.

We then investigate whether the allocation effects vary across skills. If firms compete for a short supply of skilled workers, scalability and internal ressources might affect there ability to attract skilled workers.

To address this question, we use the average number of employees at the firm level over each sub-period and across four levels of education - elementary school, middle school, high school and college - and five levels of occupation - non-skilled, semi-skilled, skilled, high-skilled workers, and managers.

Table 2 provides summary statistics on our sample of workers employed by firms in a relationship with a DB-plan bank and the control group, across levels of educations and occupations. Consistent with the statistics from the OECD, 67% of the workers in our sample do not have a high school degree in 2004 and only 11% have a college degree.

We estimate the following model for each subgroup j of workers:

$$\begin{aligned} Employment\ Growth_{f,j} = \beta \mathbb{1}_{Exposure\ to\ Capital\ Flows_f} + \mu Industry_s + \\ + \gamma FirmControls_f + \epsilon_{f,j} \end{aligned} \tag{4}$$

where $Employment\ Growth_{f,j}$ is the change in firm f's number of employees of category j between the pre and post-period using the Davis and Haltiwanger (1992) growth measure. $Industry_s$ is the vector of 52 industry dummies and $Controls_f$ is the vector of firm characteristics measured in the year 2004.

Columns 2 to 5 of Table 7 provide the results across levels of education. We observe that employment growth increases more at firms exposed to capital flows mostly for highly educated workers, while the effect for the less educated ones is smaller and only slightly significant. In particular, the elasticity of employment to the credit expansion for college-educated workers is higher than the average and equal to 45% (=3.6/8). The corresponding elasticities are equal to 26% and 22% for high school- and middle school-educated workers, respectively, and only 15% for workers with elementary school education. Overall, the effect is three times larger for workers with a college degree than for workers with up to elementary school education. The higher employment growth for college-educated workers hence accounts for more than 20% of the total effect of the credit supply shock, even though college-educated workers account only for 10% of the workforce.[27]

Then columns 6 to 10 of Table 7 provide the results across types of occupation. Firms that are more exposed to capital flows increase more the employment of workers in high-skilled occupations. There is almost no effect on workers in non-skilled occupations.

As a robustness check, Table D.5 in the online appendix restricts the sample to firms with 5 employees or more. While the effect is of relatively smaller magnitude, it is again mostly driven by educated workers employed in skill-intensive occupations. In Table D.6, we replicate the results above, using the measure of treatment intensity, instead of the treatment dummy. Again, the negative effects on high-skilled workers - defined either by education or by occupation - are the strongest. The higher the intensity of the treatment, the larger the differential effect in the growth rate of skilled employment.

5.2 Hiring across Skills

We now investigate the effects of the capital inflows on the allocation of workers and skills in worker-level regressions. These regressions allow us to better identify the effects across skills, to differentiate between worker inflows and outflows, and they alleviate concerns that the specifications at the firm level might raise. For example, if worker characteristics such as age or tenure varied across levels of education, age or tenure effects could be driving the results. We, therefore, control for polynomials of age and tenure in worker-level regressions. In addition, changes in growth rates are likely to be mechanically higher when initial values are low, hence amplifying the effect on educated workers. This concern is relevant because the share of highly-skilled or college-educated workers in 2004 in our sample is as low as 11%.[28]

[27]Table D.4 in the online appendix reproduces Table 7 using a more disaggregated classification of workers by years of education. The effects are maintained.

[28]Because you cannot lose half of a worker, when you lose one educated worker, the effect on the growth rate might be amplified. Let us consider four companies with each 4 unskilled workers, and 1 manager. Say that the probability to leave is 25% for all categories of workers.

We analyze the effects of access to capital flows on firm attractiveness to skilled workers by estimating the following specification:

$$\begin{aligned} Pr(Joiningthefirm)_{i,f,t} = {} & \beta Post_t \times \mathbb{1}_{Exposure\ to\ Capital\ Flows_f} + \\ & + \alpha Firm_f + \eta Year_t + \phi WorkerControls_{i,t} + \\ & + \gamma FirmControls_{f,t} + \epsilon_{i,f,t} \end{aligned} \tag{5}$$

$Pr(Joiningthefirm)_{i,f,t}$ is a dummy variable that takes the value one if worker i joins firm f in year t. $Post_t \times \mathbb{1}_{Exposure\ to\ Capital\ Flows_f}$ is a dummy variable that takes the value of one after 2005 if the worker leaves a firm that has been affected by the credit supply shock and zero otherwise. $Firm_f$ is a vector of firm fixed effects that accounts for time-invariant differences in turnover across firms, while $Year_t$ is a vector of year fixed effects to capture macroeconomic trends that can affect turnover. The coefficient β hence measures how the probability that a worker joins a firm varies whether the firm still benefits from capital flows or not. We also include a set of worker time-varying characteristics that could affect the probability of leaving: $WorkerControl_{i,t}$ includes a polynomial of age and tenure. The $FirmControl_{f,t}$ vector includes a large set of fixed effects that account for the evolution of the optimal composition of workers across sectors, firm size, age and ex-ante wage: year × industry, year × firm size quartiles , year × firm age quartiles, year × firm average wage quartiles, and an interaction term between firm-level product per worker in the pre-treatment period and year, in order to control for pre-exiting trends in productivity, at firm level. Our results are thus not driven by the possibility that, for example, firms that are affected by the shocks are also from industries/size quartile/age quartile/wage quartile where more educated employees are leaving. The effect is also robust to pre-existing differences in productivity level. Finally, we cluster standard errors at the banking group × industry level and results are robust to clustering at the worker level.

Table 8 reports the results. We first note that while the estimate of β in Column 1 is positive, which implies that firms exposed to capital flows attract

One firm loses 1 manager, and each firm loses one unskilled worker. Then the average growth rate is -50% for managers and -25% for unskilled workers, while the probability to leave is the same.

more employees, the magnitude is very small. An average worker is only 0.1 percentage points more likely to start working at a firm that kept being exposed to capital flows after the introduction of IAS19. However, Columns 2 to 5 indicate that the effect varies significantly by level of education. Following the shock, the probability that a firm will hire a worker with a college degree is 1.7 percentage points higher for firms exposed to capital flows.

INCLUDE TABLE 8

If workers are switching to firms with access to capital flows, we should also observe that firm in a relationship with a DB-plan bank are less likely to retain workers. We formally test whether workers are more likely to leave DB-plan bank by estimating the following panel model over the 2003-2006 period:

$$\begin{aligned} Pr(Leavingthefirm)_{i,f,t} = {} & \beta Post_t \times \mathbb{1}_{Exposure\ to\ Capital\ Flows_f} + \\ & + \alpha Firm_f + \eta Year_t + \phi WorkerControls_{i,t} + \\ & + \gamma FirmControls_{f,t} + \epsilon_{i,f,t} \end{aligned} \tag{6}$$

$Pr(Leavingthefirm)_{i,f,t}$ is a dummy variable indicating whether worker i leaves firm f in year t.

Table 9 reports the result. In Column 1, we find that lower access to capital flows is associated with an increase in the probability that workers leave the firm, as the coefficient β is negative, as well as statistically and economically significant. This estimate implies that the probability of the average worker to leave the firm is 1 percentage point higher when the firm is in a relationship with a DB-plan bank. As Table 2 shows, ex-ante, workers from treated and from control firms have the same probability of leaving.

We then show that the effect of IAS19 on the probability that a worker leaves the firm increases with the worker's skills. The results in Columns 2 to 5 of Table 9 suggest that the propensity of workers to leave firms in a relationship with a DB-plan bank is higher when workers are more educated. More precisely, the effect is twice larger for college and high-school educated workers than for workers with less than a high-school degree, with respectively a 1.4 pp and a 0.7 pp increase in the probability to leave. This result also stands across types of occupation: Columns 6 in the bottom part of the table indicates that workers in highly-skilled intensive occupations have a 2.5 percentage point higher probability to leave affected firms after the shock.

INCLUDE TABLE 9

Finally, the first panel on Figure 1 plots the dynamics of the difference in the probability to leave for college-educated workers in treated firms versus control firms. The strongest effect on leavers can be observed at the end of 2006, suggesting that the impact of the credit shock on worker separations lasts for two years.

5.3 Wage Outcome: Evidence of Competition for Skilled Workers

Are firms exposed to capital flows attracting skilled workers because they can offer higher wages? To address this question, we investigate the evolution of wages for workers who switch to firms exposed to capital flows versus regular switchers, in a triple difference-in-differences wage panel model. Existing labor literature shows that when workers exit as a result of firing or firm closures, they incur significant earning losses (Jacobson et al. 1993; Couch and Placzek 2010). However, if workers self-select into firms competing for skills, we should observe a positive effect on the wages of switchers after IAS19, and the effects should be larger for educated workers.

We identify as follows the differential effect of the credit expansion on worker wages, by analysing whether treated workers switching after the shock receive a wage premium:

$$Log(HourlyWage)_{i,t} = \beta Switcher_{i,t} \times \mathbb{1}_{Exposure\ to\ Capital\ Flows_f} \times Post_t + \alpha Switcher_{i,t} + \\ + \gamma Switcher_{i,t} \times Post_t + \theta \mathbb{1}_{Exposure\ to\ Capital\ Flows_f} \times Post_t + \\ + \mu Switcher_{i,t} \times \mathbb{1}_{Exposure\ to\ Capital\ Flows_f} + Worker_i + Year_t + \epsilon_{i,f,t} \quad (7)$$

$Log(HourlyWage)_{i,t}$ is the log of the average hourly wage of a worker i in year t.[29] $Switcher_{i,t}$ is a dummy variable indicating whether worker i switched to a different job since the previous year. We restrict the estimation sample to workers that in 2004 were employed by either a treated or a control firm. Thus, $\mathbb{1}_{Exposure\ to\ Capital\ Flows_f}$ allocates workers to 0/1 groups, depending on whether they were employed by a firm in a relationship with a DB Plan Bank or not in 2004. We then keep the full employment history of workers that appear in QP every year, since 2002 to 2007, therefore identifying switchers from 2003 to 2007. $Post_t$ is a dummy variable that takes the value of one after 2005. The coefficient β of the triple interaction $Switcher_{i,t} \times Treated_f \times Post_t$ hence measures the sensitivity of the switching wage to capital flows, by isolating the effect on workers switching firms in the post-period. We include in the estimations combinations of the variables present in the triple interaction: $Switcher_{i,t}$, $Switcher_{i,t} \times Post_t$, $\mathbb{1}_{Exposure\ to\ Capital\ Flows_j} \times Post_t$ and $Switcher_{i,t} \times \mathbb{1}_{Exposure\ to\ Capital\ Flows_f}$. The dummies $\mathbb{1}_{Exposure\ to\ Capital\ Flows_f}$ and $Post$ are included in the worker and, respectively, year fixed effects. We estimate the model for the whole sample of workers and by education. To account for the non-linear effect of age on wages, all models include a second-degree polynomial in worker age. Standard errors are clustered at worker level and reported in brackets. In Table D8 in the online appendix we cluster the same specification at two-digit industry level.

INCLUDE TABLE 10

Table 10 shows that workers that switch to firms that kept benefiting from capital flows experience a higher wage increase after the shock than previous to it

[29] The hourly wage does not include bonuses and variable income.

relative to switchers firms in a relationship with a DB-Plan Bank. Most importantly, the effect is mostly driven by high-school and college educated workers who experience a 2.7% and, respectively, 2.4% increase in wages after leaving affected firms. This result confirms that compensation is one of the driver of the allocation of skills in an economy facing large capital inflows.

6 Conclusion

Using exogenous variations in bank ability to channel capital inflows, we document how access to capital flows affects the allocation of skills in an economy. We show that the resulting credit expansion affects not only the allocation of capital and labour, but also of skills. Skilled workers are more likely to switch to less productive firms and to the non-tradable sector in periods of large capital inflows. This outcome could reduce even further the potential for future productivity growth.

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A. FIGURES

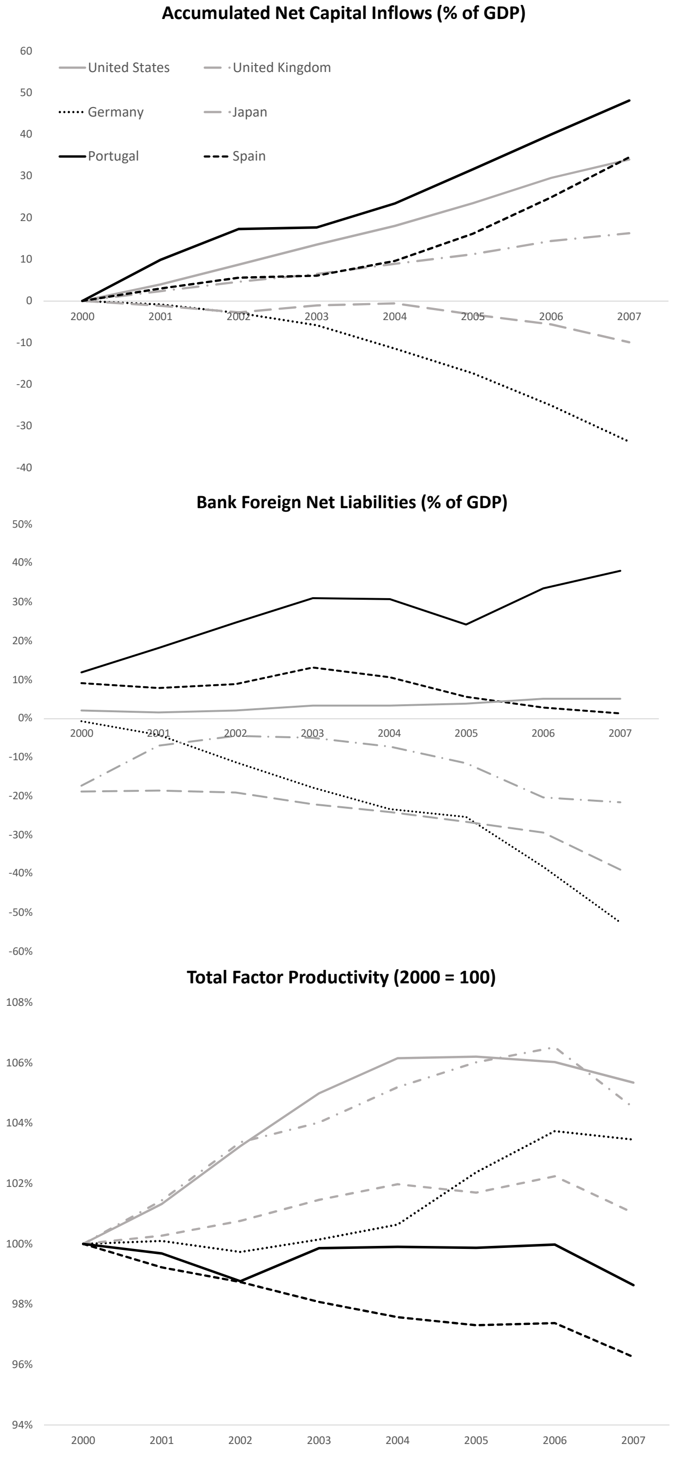


Figure 1. Net Capital Inflows, the Banking Channel and TFP across Countries

Sources: IMF `https://www.imf.org/en/Publications/WP/Issues/2016/12/31/Capital-Flows-are-Fickle-Anytime-Anywhere-40885`, Federal Reserve Bank of Saint-Louis, Bank of International Settlements, and OECD.

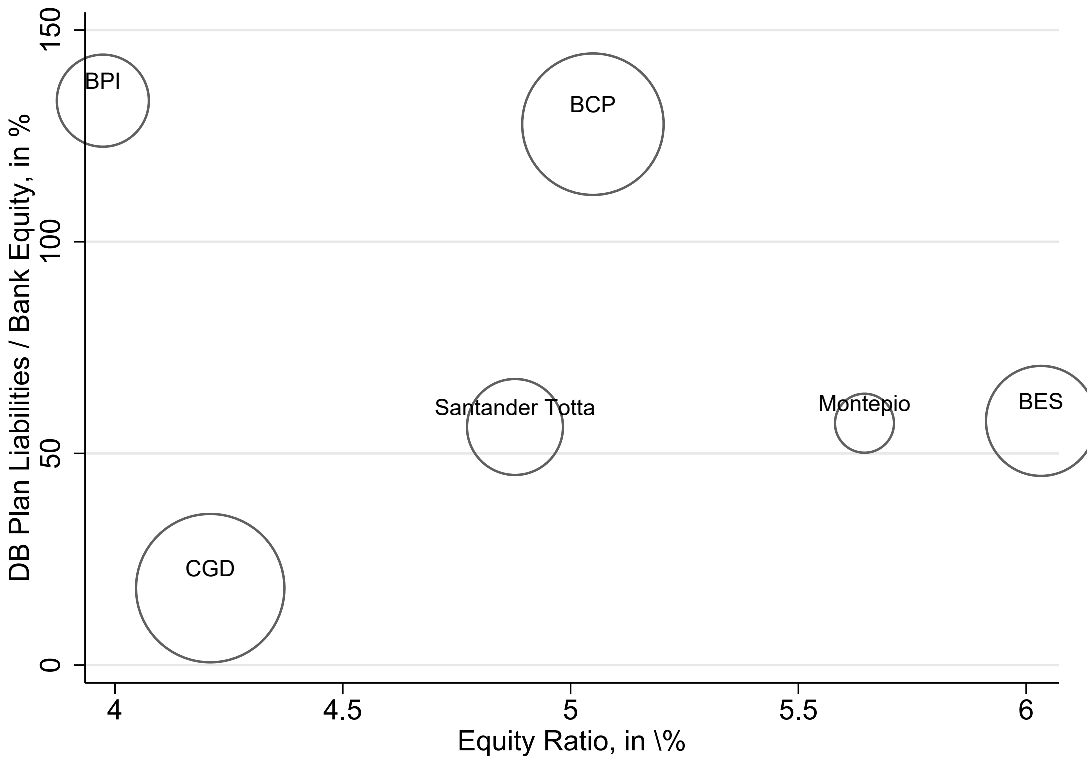
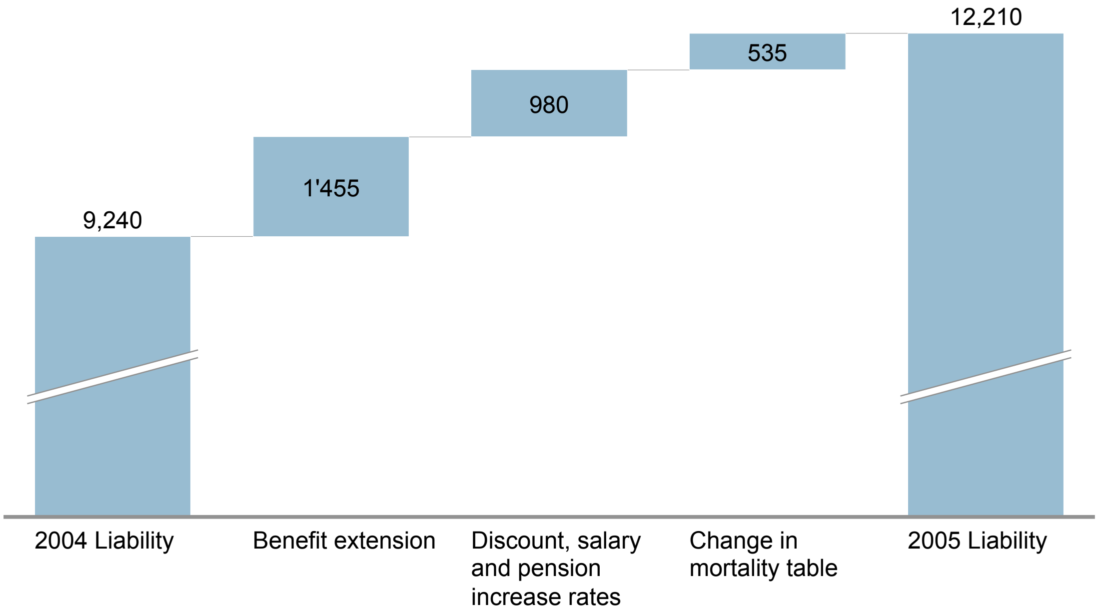


Figure 2. The Heterogeneous Exposure of the 6 Main Portuguese Banks to their DB Plans

This figure shows bank exposure to DB plans - measured as the ratio of the pension plan liabilities to bank total equity - for the 6 main Portuguese banks at the end of 2004 as a function of their equity ratio in 2004. The size of the symbol is proportional to the bank total assets. These 6 banks stand for 87% of total bank assets in Portugal. Data comes from the 2004 annual reports.

Panel A. The Effects on DB Plan Pension Liabilities



Panel B. The Effects on Bank Direct Contributions

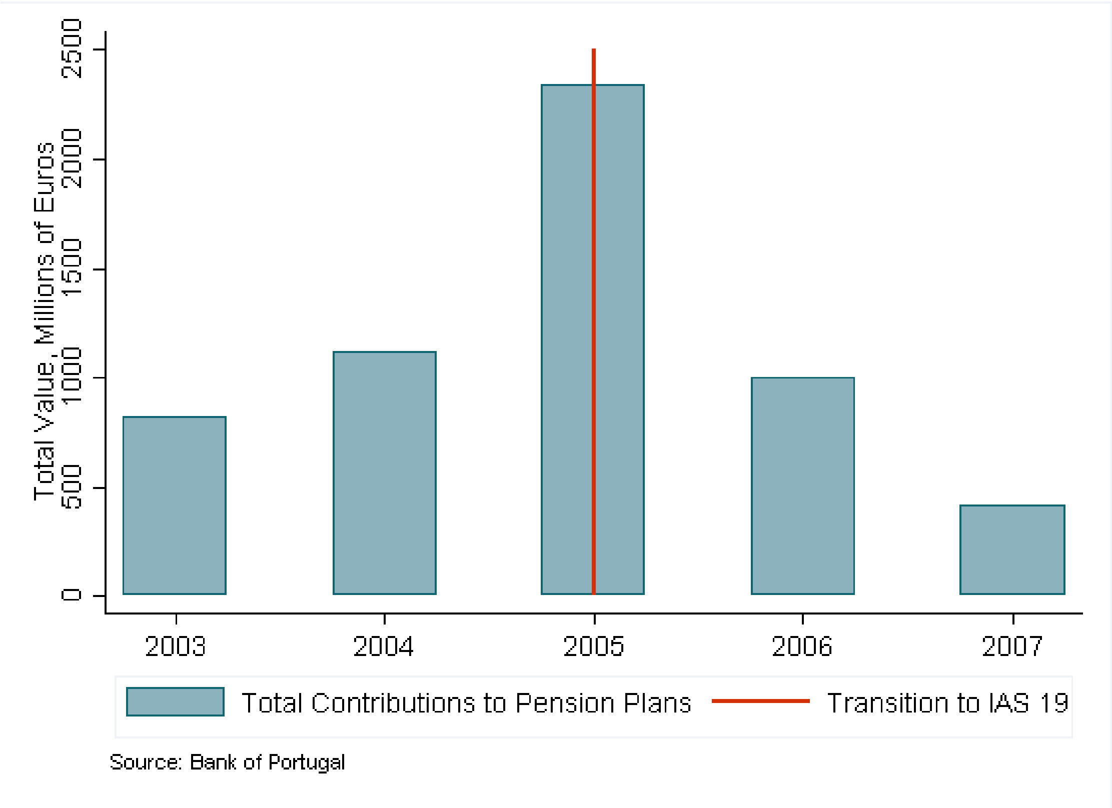


Figure 3. The Effects of the New Accounting Standards on the DB Plan Pension Liability of Portuguese Banks and their Direct Contributions to the DB Plans

Panel A illustrates the effect of the introduction of IAS 19 on the aggregated bank DB plan liabilities and decomposes the effects across its main channels. The introduction of IAS 19 resulted in a 30% increase in bank DB plan liabilities. Panel B shows the aggregate value of bank annual cash contributions to their DB pension plans over the 2003-2007 period. Legislation on privately funded pension plans in Portugal requires the pension benefit obligations to be funded at 100% for pensions in payment, and at 95% for employees in service.

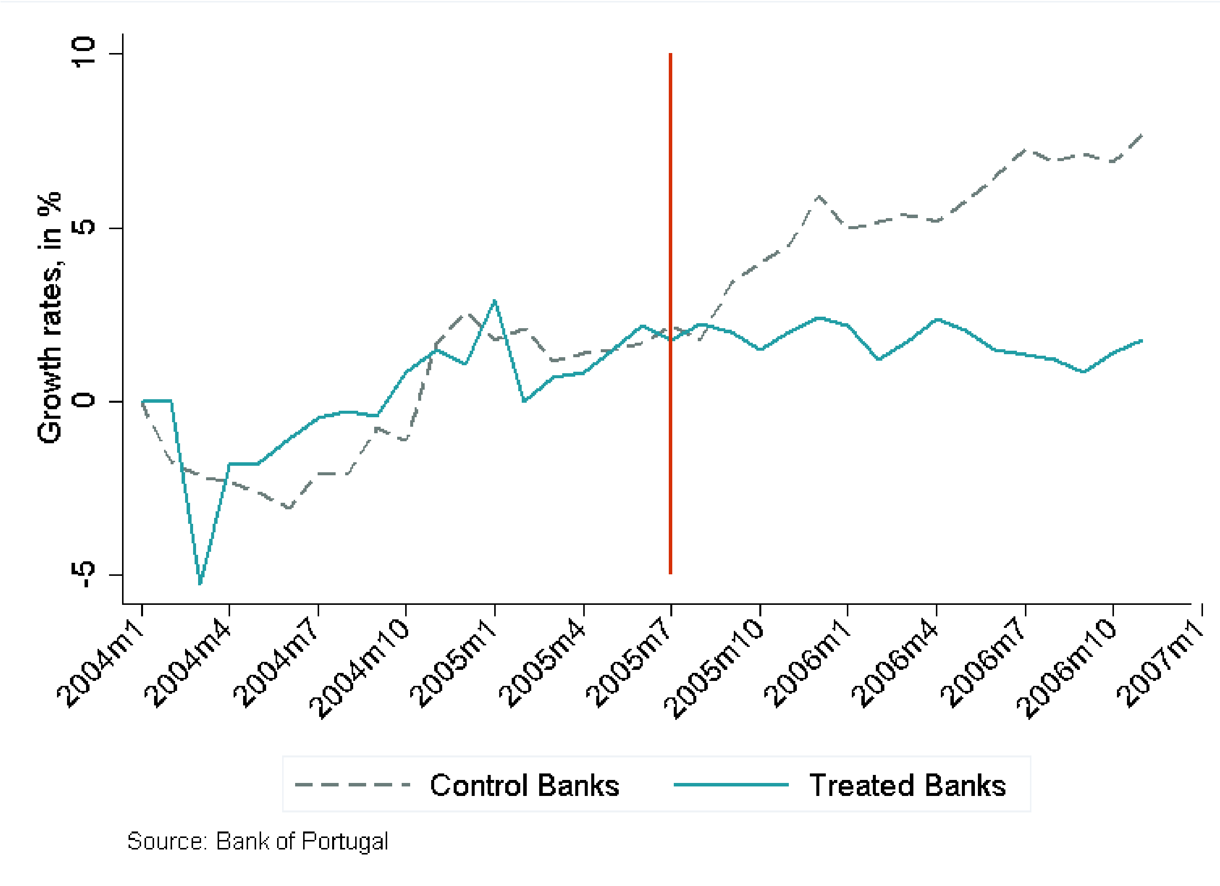


Figure 4. Evolution of Credit: Treated versus Control Banks

This figure captures the evolution of credit granted by treated and non-treated banks from January 2004 to January 2007. The two lines represent the percentage growth in credit since 2004 on a monthly basis. While credit granted by the two groups of banks evolves in parallel until 2005, since then credit exposures from treated banks experience visibly lower growth than controls.

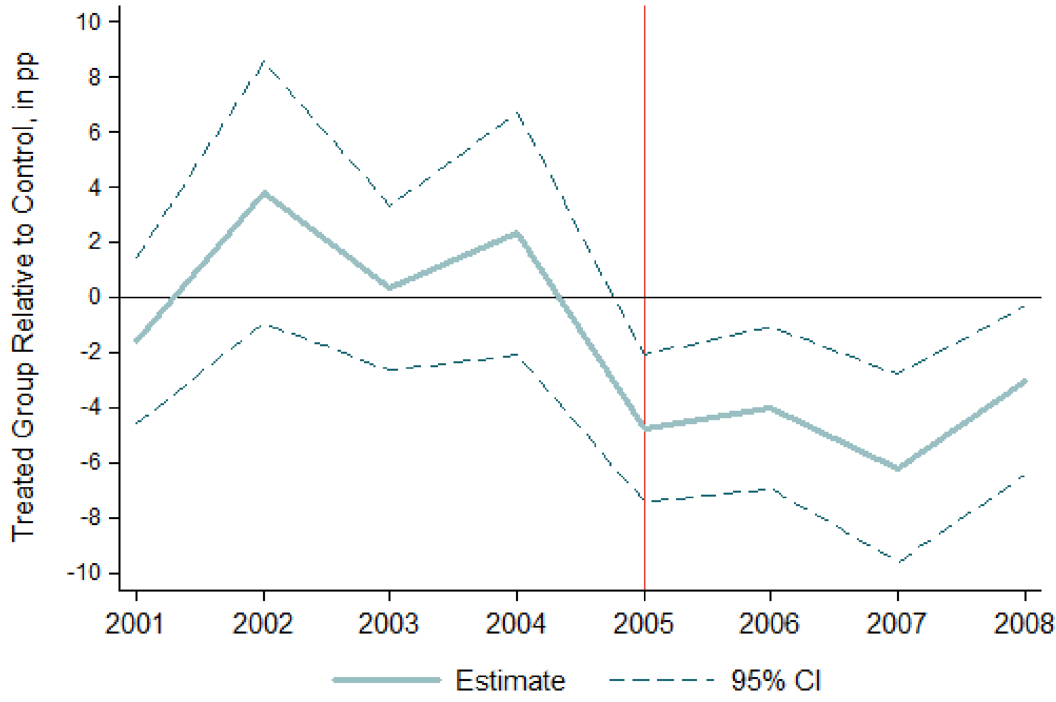


Figure 5. Difference in the Yearly Growth Rate in Borrowing between Firms in a Relationship with a DB-plan bank and the Control Group

This figure captures the yearly dynamics of β in the following panel model where the dependant variable is the yearly growth rate in credit exposure at the firm level and *Treated* indicates firms in a relationship with a DB-plan bank (affected by IAS19).

$$\%Growth\ in\ Credit\ Exposure_{f,y} = \beta_y Treated_f + \\ + \eta YearFE + \gamma_{y,f} FirmControls + e_{f,y}$$

B. TABLES

Table 1. Summary Statistics: Banks and Firms

	N (1)	Mean (2)	SD (3)	P10 (4)	P50 (5)	P90 (6)
Bank DB Plan Characteristics						
Ratio of Bank Pension Liabilities to Bank Equity *(Treatment Intensity)*	333,788	0.40	0.32	0	0.40	1.04
Bank Characteristics - DB-plan Banks						
Log(Total Assets) (EUR 000)	13	8.09	1.73	5.65	7.98	10.34
Capital Ratio	13	.08	.04	.03	.09	.13
Liquidity Ratio	13	.19	.18	.04	.14	.46
Loans to Assets	13	.74	.19	.55	.79	.93
Short Term Liabilities to Assets	13	.17	.13	.01	.19	.35
Bond Funding Ratio	13	.07	.09	.01	.06	.24
Doubtful Ratio	13	.01	.01	0	.01	.03
Bank Characteristics - Control Banks						
Log(Total Assets) (EUR 000)	46	6.36	1.92	4.07	6.01	8.76
Capital Ratio	46	.11	.10	.06	.09	.24
Liquidity Ratio	46	.22	.21	.01	.14	.53
Loans to Assets	46	.79	.20	.47	.87	.98
Short Term Liabilities to Assets	46	.15	.12	.0.01	.14	.31
Bond Funding Ratio	46	.03	.06	0	.01	.06
Doubtful Ratio	46	.02	.04	.01	0.01	.06
Firm Exposure to Bank DB Plans						
Treatment Intensity	161,202	.39	.28	.016	.40	.79
Treatment Dummy	161,202	.50	.49	0	1	1
Firm Characteristics - Firms in a relationship with DB-Plan Banks						
Total Sales (EUR 000)	80,846	758.47	2,105.67	10.78	175.01	1,531.79
Firm Age	80,846	11.70	14.09	2	8	26
% Foreign Ownership	80,846	1.86	12.98	0	0	0
% Public Ownership	80,846	.15	3.51	0	0	0
Months in the CR	80,846	72.91	40.72	16	75	120
Average Monthly Credit (Log EUR)	80,846	5.23	5.77	3.28	4.39	5.47
Current Default Dummy	80,846	.04	.20	0	0	0
Past Default Dummy	80,846	.09	.28	0	0	0
Number of Workers	80,846	12.61	81.99	1	4	20
- with low education	80,846	3.18	22.23	0	0	6
- with middle education	80,846	5.26	41.04	0	2	9
- with highschool	80,846	2.49	23.65	0	1	4
- with college	80,846	1.38	14.62	0	0	2
Average Sales per Worker (EUR 000)	80,846	87.70	422.60	3.78	37.87	164.07
Average Hourly Wage (EUR)	80,846	3.96	3.74	0	3.36	6.68
Average Workforce Tenure	80,846	5.72	4.84	1.02	4.22	12.59
Average Workforce Age	80,846	39.24	7.62	30	38.67	49.42
Firm Characteristics - Control Group						
Total Sales (EUR 000)	80,356	915.08	2,393.78	13.29	191.87	1,966.48
Firm Age	80,356	11.58	15.68	2	8	25
% Foreign Ownership	80,356	1.04	9.65	0	0	0
% Public Ownership	80,356	.25	4.73	0	0	0
Months in the CR	80,356	73.14	40.67	17	75	120
Average Monthly Credit (Log EUR)	80,356	5.46	5.91	3.66	4.59	5.79
Current Default Dummy	80,356	.08	.27	0	0	0
Past Default Dummy	80,356	.15	.35	0	0	1
Number of Workers	80,356	15.35	113.93	1	5	25
- with low education	80,846	4.09	24.21	0	1	8
- with middle education	80,846	6.45	46.42	0	2	11
- with highschool	80,846	2.86	37.99	0	1	4
- with college	80,846	1.56	23.42	0	0	2
Average Sales per Worker (EUR 000)	80,356	89.70	333.58	4.41	39.27	175.76
Average Hourly Wage (EUR)	80,356	3.61	2.55	0	3.35	6.35
Average Workforce Tenure	80,356	5.43	4.50	1.08	4.08	11.75
Average Workforce Age	80,356	38.82	7.37	30	38.25	48.5

This table reports summary statistics for all bank-firm credit exposures, bank and DB-pla,n plan data as well as firm characteristics in 2004, the year before the shock. Banks and firms are separated in treatment and control groups as described in Section 3.3.

Table 2. Summary Statistics: Workers

	N	Mean	SD	P10	P50	P90
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Worker Characteristics - Firms in a relationship with DB-Plan Banks						
Probability to Leave	929,861	.22	.42	0	0	1
Probability to Enter	929,861	.25	.44	0	0	1
Probability to Switch	929,861	.08	.27	0	0	1
Hourly Wage (2004 Euros)	929,861	5.84	8.49	2.54	4.05	10.5
Years of Education (Starting at 6)	929,861	8.14	4.01	4	9	15
Gender (1=Male; 2=Female)	929,861	1.42	.49	1	1	2
Age	929,861	38.40	11.23	25	37	54
Tenure in Firm	929,861	7.68	8.30	0.5	4.58	19.08
Worker Characteristics - Control Group						
Probability to Leave	1,127,250	.22	.42	0	0	1
Probability to Enter	1,127,250	.25	.43	0	0	1
Probability to Switch	1,127,250	.08	.26	0	0	1
Hourly Wage (2004 Euros)	1,127,250	5.97	8.58	2.54	4.08	11.13
Years of Education (Starting at 6)	1,127,250	7.96	4.00	4	6	12
Gender (1=Male; 2=Female)	1,127,250	1.39	.49	1	1	2
Age	1,127,250	38.52	11.21	25	37	54
Tenure in Firm	1,127,250	8.02	8.57	0.5	4.75	20.92

This table reports summary statistics for all workers of treated and control firms in 2004. A total of 2,196,014 workers is separated into treated and control groups based on the treatment of their employer.

Table 3. The Introduction of IAS 19: Description of the Treatment

Timeline	
Implementation of IAS19	January-June 2005
Pre-treatment Period	Year 2004
Post-treatment Period	Years 2005-2006
The Effect on Banks	
DB-plan Banks	
Number	13
% of Total Credit	56
Control Banks	
Number	46
% of Total Credit	44
Effect on Bank Internal Funds	
2005 Contribution to DB Plans	
2005 Total Amount, bln euros	2.3
Percentage of Treated Bank Equity	21
2005 Prudential Deductions	
Total Amount, bln euros	1.5
Percentage of Treated Bank Equity	14
Main Effect on Bank Credit Expansion	
Change in Credit Growth for DB-Plan Banks	-17 pp
The Effect on Firms	
Treatment Variables	
% firms in a relationship with DB-plan banks	0.5
Main Effect on Credit Growth	
Increase in Credit Growth for Firms still Exposed to Capital Flows	+8 pp
Main Effect on Employment for firms still exposed to capital flows	
Variation in Total Employment Growth	+1.7 pp
Inferred Effect on Total Employment Growth of a 10 pp Increase in Credit Expansion	+ 1.9 pp

This table summarizes the characteristics and the main effects of the introduction of IAS 19 on bank credit expansion. Effects are computed using the estimation results in Table 4 (column 8), Table 5 (column 3) and Table 7 (column 1).

Table 4. The Impact of the Introduction of IAS 19 on Bank Credit Expansion

	Bank-Firm Credit Growth, in %				New Lending	End Lending
Sample	All			*Treatment>0*		
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}_{DB-PlanBank}$	-16.8***	-18.9***			-0.550***	0.167***
	(2.9)	(2.9)			(0.062)	(0.043)
Bank Exposure to DB Plan			-10.9***	-18.1***		
			(4.1)	(6.3)		
Firm Characteristics	Yes	-	-	-	Yes	Yes
Firm Fixed Effects	-	Yes	Yes	Yes	-	-
Bank Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Observations	333,788	269,181	319,197	236,685	426,119	426,119
R^2	0.063	0.413	0.455	0.489		
Pseudo-R^2					0.236	0.031

This table reports the coefficients of OLS and Logit estimations where the unit of observation is the loan exposure at the bank-firm level. The dependent variable is the growth of the loan exposure between the pre-treatment period (2004) and the post treatment period (2005 - 2006) in Columns 1 to 4, in %. In Columns 5 and 6, the dependent variables are dummy variables that indicate respectively whether a new loan is granted to a firm with currently zero exposure to the credit-granting bank and whether an existing loan exposure ends in the post-period. The independent variable $BankExposuretoDBPlan$ is the ratio of bank pension liabilities to bank total equity in the *pre-period*, while the variable $\mathbb{1}_{DB-PlanBank}$ allocates banks into treatment and control groups, at the median of the $BankExposuretoDBPlan$ variable. The sample comprises the universe of bank-firm exposures over the 2004-2006 period for firms from the private sector with at least one employee and positive exposure in 2004. Column 4 restricts the analysis only to bank-firm credit exposures covered by banks with a positive pension treatment. Bank characteristics include the logarithm of assets, capital ratios, liquidity ratios, loan-to-asset ratios, short term liabilities to assets, bond funding to assets, and non performing loan ratios in 2004, as well as the categorical controls for the type of credit institution. In the specifications without firm fixed effects, firm controls include our measures of the firm credit history, i.e. average volumes of credit over the previous 10 years, the number of months with positive credit exposures, and indicators for past and current defaults, the logarithm of total sales, firm age, product per worker and workforce tenure, as well as indicators for legal organization and ownership structure. Standard errors are clustered at banking group×industry levels and are reported in brackets, $^{\star}p < 0.10, ^{\star\star}p < 0.05, ^{\star\star\star}p < 0.01$

Table 5. Capital Inflows and Firm Borrowing

	Credit Growth at Firm Level					
	All Firms				Non Tradable	Tradable
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}_{Capital\ Flows\ Exposure}$	8.0***	6.6***			11.0***	5.1***
	(1.5)	(1.3)			(1.1)	(1.0)
Capital Flows Exposure (Intensity)			18.6***	15.0***		
			(2.1)	(2.4)		
Firm Characteristics	-	Yes	Yes	Yes	Yes	Yes
Bank Characteristics	-	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	-	Yes	-	-
Observations	161,202	161,202	161,202	161,202	86,632	25,371
R^2	0.002	0.076	0.080	0.082	0.081	0.082

This table reports the coefficients of OLS regressions where the dependent variable is the growth of firm total credit exposure between the pre-treatment period, 2004, and the post treatment period, 2005-2006. The independent variable, $\mathbb{1}_{Capital\ Flows\ Exposure}$ identifies firms that are not exposed to DB-plan banks, and hence kept being exposed to capital flows after 2005. We start with a simple difference-in-difference estimation in columns 1 and 3 and we add firm controls, i.e. our measures of credit history, the logarithm of total sales, firm age, product per worker and workforce tenure, as well as indicators for legal organization and ownership structure, and bank characteristics, i.e. the logarithm of assets, capital ratios, liquidity ratios, loan-to-asset ratios, short term liabilities to assets, bond funding to assets, and non performing loan ratios in 2004 - weighted by each bank's credit exposure in a firm's total credit in the same year - in columns 2 and 4. In columns 5 and 6 we restrict the sample to the non-tradable - including hospitality and food, wholesale and retail, transportation and storage and construction - and the tradable sectors, respectively . Standard errors are clustered at banking group $\times$ industry levels and reported in brackets, $^{\star}p < 0.10$, $^{\star\star}p < 0.05$, $^{\star\star\star}p < 0.01$

Table 6. Capital Inflows and Firm Employment: Effects across Education Levels and Occupations

	Employment Growth at the Firm Level, in %				
		By Education Level			
	All Workers (1)	College Degree (2)	High School Degree (3)	Middle School (4)	Up to Elementary School (5)
$\mathbb{1}_{Capital\ Flows\ Exposure}$	1.7***	3.6***	2.1***	1.8***	1.2*
	(0.3)	(0.9)	(0.7)	(0.5)	(0.6)
Firm Characteristics	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	161,202	59,421	96,174	131,094	93,562
R^2	0.602	0.291	0.331	0.258	0.386
		By Occupation Type			
	Management (6)	Highly-Skilled Intensive (7)	Skilled Intensive (8)	Semi-Skilled Intensive (9)	Non-Skilled (10)
$\mathbb{1}_{Capital\ Flows\ Exposure}$	1.3***	2.0**	0.1	1.6***	0.2
	(0.5)	(0.8)	(0.6)	(0.5)	(1.0)
Firm Characteristics	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	140,849	44,578	125,712	63,859	55,619
R^2	0.167	0.071	0.143	0.075	0.059

This table reports the coefficients of OLS regressions where the dependent variable is the growth rate of employment at the firm level between the pre-period (2004) and the post-period (2005 to 2006). The independent variable $\mathbb{1}_{Capital\ Flows\ Exposure}$ indicates firms that are still exposed to capital flows after 2005. All specifications are saturated with 52 two-digit industry fixed effects and control for the full set of firm characteristics available in 2004: the four measures of firm credit history, the logarithm of total sales, firm age, product per worker and workforce tenure, as well as indicators for the legal organization and the ownership structure. The initial sample includes all private firms from the non-financial sector which in 2004 had positive credit exposure and hired at least one worker. In Columns 2 to 10 the sample is restricted to firms hiring at least one worker with the specified education level or type of occupation over the three years of analysis. Standard errors are clustered at banking group × industry levels and reported in brackets, $^{\star}p < 0.10$, $^{\star\star}p < 0.05$, $^{\star\star\star}p < 0.01$

Table 7. Capital Inflows and Firm Employment: Tradable versus non Tradable Sectors

	Employment Growth at the Firm Level, in %			
	By Education Level			
	College Degree (1)	High School Degree (2)	Middle School (3)	Up to Elementary School (4)
$\mathbb{1}_{Capital\ Flows\ Exposure} \times$ *Nontradable*	4.8***	3.8	3.2	0.00
	(1.2)	(1.38)	(2.6)	(0.28)
$\mathbb{1}_{Capital\ Flows\ Exposure}$	1.9	0.00	-0.00	0.00
	(0.9)	(0.9)	(0.7)	(0.5)
NonTradable	-0.00	-0.04	-0.18	0.00
	(-0.37)	(-0.05)	(-0.20)	(-0.00)
Firm Characteristics	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Observations	34,921	64,382	96,439	71,317
R^2	0.602	0.291	0.331	0.258
	By Occupation Type			
	Highly-Skilled Intensive (6)	Skilled Intensive (7)	Semi-Skilled Intensive (8)	Non-Skilled (9)
$\mathbb{1}_{Capital\ Flows\ Exposure} \times$ *Nontradable*	2.5***	-0.00	1.2	-0.00
	(0.8)	(-0.0)	(0.7)	(-0.00)
$\mathbb{1}_{Capital\ Flows\ Exposure}$	0.00	0.00	0.00	0.00
	(0.0)	(0.0)	(0.0)	(0.0)
NonTradable	-0.00	-0.00	8.7***	-0.05*
	(0.0)	(-0.0)	(2.3)	(-0.03)
Firm Characteristics	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Observations	101,940	91,571	96,174	131,094
R^2	0.602	0.291	0.331	0.258

This table reports the coefficients of OLS regressions where the dependent variable is the growth rate of employment at the firm level between the pre-period (2004) and the post-period (2005 to 2006) across level of educations and occupations. The independent variable $\mathbb{1}_{Capital\ Flows\ Exposure}$ indicates firms that are still exposed to capital flows after 2005. All specifications control for the full set of firm characteristics available in 2004: the four measures of firm credit history, the logarithm of total sales, firm age, product per worker and workforce tenure, as well as indicators for the legal organization and the ownership structure. The initial sample includes all private firms from the tradable/nontradable sectors which in 2004 had positive credit exposure and hired at least one worker. Standard errors are clustered at banking group × industry levels and reported in brackets, $^{\star}p < 0.10$, $^{\star\star}p < 0.05$, $^{\star\star\star}p < 0.01$

Table 8. Capital Inflows and Worker Allocation: Hiring across Education Levels and Occupations

	Dummy Variable=1 if the employee is new to the firm, 0 if not				
		By Education Level			
	All Workers (1)	College Degree (2)	High School Degree (3)	Middle School (4)	Up to Elementary School (5)
Post × $\mathbb{1}_{Capital\ Flows\ Expposure}$	0.001***	0.017***	0.006***	-0.005***	0.001
	(0.000)	(0.002)	(0.001)	(0.001)	(0.001)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
Worker Characteristics	Yes	Yes	Yes	Yes	Yes
Year*Industry FE	Yes	Yes	Yes	Yes	Yes
Year*Firm Size FE	Yes	Yes	Yes	Yes	Yes
Year*Firm Age FE	Yes	Yes	Yes	Yes	Yes
Year*Firm Wage FE	Yes	Yes	Yes	Yes	Yes
Year*Firm Productivity	Yes	Yes	Yes	Yes	Yes
Observations	7,875,424	873,317	1,616,382	3,427,894	1,923,440
R^2	0.373	0.379	0.423	0.401	0.386
	By Occupation Type				
	Management (6)	Highly-Skilled Intensive (7)	Skilled Intensive (8)	Semi-Skilled Intensive (9)	Non-Skilled (10)
Post × $\mathbb{1}_{Capital\ Flows\ Exposure}$	0.007***	0.009***	-0.000	0.007***	-0.005***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
Worker Characteristics	Yes	Yes	Yes	Yes	Yes
Year*Industry FE	Yes	Yes	Yes	Yes	Yes
Year*Firm Size FE	Yes	Yes	Yes	Yes	Yes
Year*Firm Age FE	Yes	Yes	Yes	Yes	Yes
Year*Firm Wage FE	Yes	Yes	Yes	Yes	Yes
Year*Firm Productivity	Yes	Yes	Yes	Yes	Yes
Observations	1,471,296	553,660	3,118,535	1,236,680	915,451
R^2	0.336	0.369	0.373	0.407	0.454

This table reports the coefficients of a linear model estimating the probability that a worker enters a firm in the sample. The dependent variable is a dummy variable equal to 1 for the first year a worker enters a firm, and 0 for existing workers. The independent variable $\mathbb{1}_{Capital\ Flows\ Exposure}$ allocates workers into two groups, depending on whether the firm they are entering kept being exposed to capital flows after 2005. The estimations are based on panel analysis, including a pre and a post period. The pre-period includes 2003 and 2004. The post-period includes 2005 and 2006. All specifications are saturated with firm and year fixed effects, year×industry fixed effects, as well as fixed effects for the interaction between year and quartiles for the main firm characteristics (size, age, and average hourly wage in the pre-period). In addition, all models include an interaction term between product per worker and year, in order to control for pre-exiting trends in productivity, at firm level. Worker characteristics include a polynomial of age and gender. The initial sample includes all private firms from the non-financial sector which in 2004 had positive credit exposure and hired at least one worker. In Columns 2 to 10 the sample is restricted by worker education and occupation. Standard errors are clustered at banking group × industry and reported in brackets. $^{\star}p < 0.10$, $^{\star\star}p < 0.05$, $^{\star\star\star}p < 0.01$.

Table 9. Capital Inflows and Worker Allocation: Separations across Education Levels and Occupations

	Dummy=1 if the Employee Leaves the Firm, 0 if not				
		By Education Level			
	All Workers (1)	College Degree (2)	High School Degree (3)	Middle School (4)	Up to Elementary School (5)
Post × $\mathbb{1}_{Capital\ Flows\ Exposure}$	-0.010***	-0.013***	-0.014***	-0.006***	-0.008***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
Worker Characteristics	Yes	Yes	Yes	Yes	Yes
Year*Industry FE	Yes	Yes	Yes	Yes	Yes
Year*Firm Size FE	Yes	Yes	Yes	Yes	Yes
Year*Firm Age FE	Yes	Yes	Yes	Yes	Yes
Year*Firm Wage FE	Yes	Yes	Yes	Yes	Yes
Year*Firm Productivity	Yes	Yes	Yes	Yes	Yes
Observations	7,875,424	873,317	1,616,382	3,427,894	1,923,440
R^2	0.249	0.246	0.293	0.272	0.270
	By Occupation Type				
	Management (6)	Highly-Skilled Intensive (7)	Skilled Intensive (8)	Semi-Skilled Intensive (9)	Non-Skilled (10)
Post × $\mathbb{1}_{Capital\ Flows\ Exposure}$	- 0.008***	-0.025***	- 0.006***	-0.005***	-0.021***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
Worker Characteristics	Yes	Yes	Yes	Yes	Yes
Year*Industry FE	Yes	Yes	Yes	Yes	Yes
Year*Firm Size FE	Yes	Yes	Yes	Yes	Yes
Year*Firm Age FE	Yes	Yes	Yes	Yes	Yes
Year*Firm Wage FE	Yes	Yes	Yes	Yes	Yes
Year*Firm Productivity	Yes	Yes	Yes	Yes	Yes
Observations	1,471,296	553,660	3,118,535	1,236,680	915,451
R^2	0.249	0.270	0.272	0.293	0.246

This table reports the coefficients of a linear model estimating the probability that a worker leaves a job. The dependent variable is a dummy variable equal to 1 when a worker leaves their firm, and 0 if the worker stays with the same firm. The independent variable $\mathbb{1}_{Capital\ Flows\ Exposure}$ allocates workers into two groups, depending on whether the firm they are entering kept being exposed to capital flows after 2005. The estimations are based on panel analysis, including a pre and a post period. The pre-period includes 2003 and 2004. The post-period includes 2005 and 2006. All specifications are saturated with firm and year fixed effects, year*industry fixed effects, as well as fixed effects for the interaction between year and quartiles for the main firm characteristics (size, age, and average hourly wage, in the pre-period). In addition, all models include an interaction term between sales per worker and year, in order to control for pre-exiting trends in productivity, at firm level. Worker characteristics include a polynomial of age and gender. The initial sample includes all private firms from the non-financial sector which in 2004 had positive credit exposure and hired at least one worker. In Columns 2 to 10 the sample is restricted by worker education and occupation. Standard errors are clustered at banking group × industry levels and reported in brackets. $^{\star}p < 0.10$, $^{\star\star}p < 0.05$, $^{\star\star\star}p < 0.01$.

Table 10. The Wage Outcome of Reallocations by Education Level

	Log(hourly wage)				
	All Workers (1)	College Degree (2)	High School Degree (3)	Middle School (4)	Up to Elementary School (5)
Switcher $\times \mathbb{1}_{Capital\ Flows\ Exposure} \times$ Post	0.016***	0.024***	0.027***	0.002	-0.004
	(0.002)	(0.007)	(0.005)	(0.004)	(0.005)
Switcher	-0.006***	0.003	-0.004**	-0.012***	-0.011***
	(0.001)	(0.003)	(0.002)	(0.001)	(0.002)
Switcher $\times$ $\mathbb{1}_{Capital\ Flows\ Exposure}$	-0.007***	-0.011***	-0.017***	-0.001	0.002
	(0.001)	(0.003)	(0.002)	(0.002)	(0.003)
Switcher $\times$ Post	0.004***	0.010*	-0.002	0.010***	0.012***
	(0.002)	(0.005)	(0.004)	(0.002)	(0.003)
$\mathbb{1}_{Capital\ Flows\ Exposure}$ $\times$ Post	-0.002***	-0.012***	-0.010***	0.001	0.002***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Worker Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	5,329,307	555,176	1,058,686	2,199,982	1,321,446
R^2	0.909	0.899	0.901	0.875	0.858

This table reports the coefficients of a long term wage panel model, from 2002 to 2007, estimating the wage premium or discount when workers switch firms. The main dependent variable is the logarithm of average hourly wage at worker level. The main explanatory variable, Switcher $\times \mathbb{1}_{Capital\ Flows\ Exposure} \times$ Post, is an indicator for workers who switch away to firms that are still exposed to capital flows after 2005, as not in a relationship with a DB-Plan bank. We include dummies for the double interactions, as well as a dummy for *Switchers*. The dummies for $\mathbb{1}_{Capital\ Flows\ Exposure}$ and *Post* are included in the worker and, respectively, year fixed effects. The sample includes workers 1/ that were employed in 2004 at either treated or non-treated firms and, 2/ for which we have information on the yearly labor market history. We therefore work with a fully balanced panel at the worker-year level. In Columns 2 to 5, the sample is restricted to workers of each specified level of education. All models include a second-degree polynomial in worker age. Standard errors are clustered at worker level and reported in brackets. $^{\star}p < 0.10$, $^{\star\star}p < 0.05$, $^{\star\star\star}p < 0.01$

CDS Market Structure and Bond Spreads*

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Abstract

This paper studies the effects of a supply shock in the liquidity of credit default swap (CDS) markets on bond spreads. Using as a laboratory the universe of CDS transactions done by German banks, our model is identified by the changes in CDS market liquidity due to the exit of a large dealer. We find that the CDS market converges to a new equilibrium, where traded volumes are lower and bid-ask spreads are higher. Bond yields increase in response, with stronger effects for the non-investment-grade class. Individual portfolio data indicate that the effect is partly driven by investors decreasing their holdings of both CDS and related bonds. We, therefore, show that derivative markets can affect demand in underlying securities and, subsequently, the issuers' cost of capital.

Keywords: credit default swaps, dealer markets, bonds markets, credit risk, DTCC

JEL classification: G11, G18, G20, G28

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1 Introduction

Has the development of the CDS market benefited bond markets? This question is still largely unanswered. In theory, CDS contracts serve to complete markets by offering new hedging opportunities to bond holders. Therefore, liquidity and demand should both increase in bond markets, allowing firms to have a better access to debt. Others argue, however, that by offering new opportunities to speculating investors to trade credit risk, CDS markets are in fact a substitute to bond markets. In that case, CDS markets might negatively affect the liquidity and demand for bonds. This paper uses a quasi-natural experiment to assess the role of CDS markets for bond markets, along with the implications for firms' cost of capital.

Our empirical laboratory is the universe of CDS transactions done by German banks, available at the Deutsche Bundesbank. We study how bond spreads and investor bond holdings respond to a CDS liquidity shock due to the exit of a large dealer. Because the dealer exit was sudden and motivated by capital needs, it provides the necessary source of exogenous variation. Market making requires keeping large inventories of securities, which makes it very expensive in terms of leverage and capital requirements.[1]

In our identification strategy, we exploit unique information on the CDS exposure of the dealer across underlying entities before the shock. While a growing number of papers have been using CDS transaction data (Siriwardane 2019; Eisfeldt et al. 2018), we are the first to measure the effects of a liquidity shock in the CDS market on the yields of the underlying bonds, as well as on investor portfolios. Our measure of treatment is the ex-ante market share of the dealer across underlying entities. With this measure, we investigate the impact on CDS and corporate bond markets in a difference-in-differences framework. We then study the mechanics of the effect with individual portfolio holdings of CDSs and bonds. For this, we can uniquely study the bond holdings of investors that are active traders in CDS, by merging the CDS data with monthly security holdings

[1] In fact, market-making is one of the investment banking activities with the lowest revenue returns on regulatory exposures: as capital requirements increase, the return on inventories decreases.

of German banks, also available at the Bundesbank.

The results reveal that negative liquidity shocks in the CDS market have a negative impact on bond spreads, suggesting complementaries between the two markets. Following the withdrawal, CDS contracts exposed to the shock become less liquid. In particular, a large exposure of the dealer ex ante predicts that buyside investors pay higher transaction costs and trade lower volumes ex post. Our findings support the predictions of theoretical models of search frictions (Duffie et al. 2005) and slow moving capital (Duffie 2010; Duffie and Strulovici 2012).

Subsequently, we document significant spillover effects on bond markets. The yields on the most affected bonds increase. Studying individual bond portfolios suggests that hedging motives are the ones driving the findings. German banks who had previously held the underlying bonds and protection CDSs on the same firm reduce their holdings in both instruments. The effects are more pronounced for the relatively riskier bonds, but medium and lower investment grades are also affected.

There are three reasons why data uniquely available at the Bundesbank offers the ideal laboratory to measure the costs of liquidity shocks in the CDS market. First, in its supervisory role, the Bundesbank collects from the Trade Information Warehouse (TIW) of the Depository Trust and Clearing Corporation (DTCC) granular OTC market transaction and position data for all monetary and financial institutions based in Germany.[2] Our focus is on the CDS market which is both closely related to the bond market,[3] and highly concentrated, with the five largest dealers supplying 75% of the liquidity in the single-names segment (Siriwardane 2019). Second, our measure of treatment relies on the ex-ante trading intensity in CDS of a dealer-bank headquartered in Germany, and we obtain detailed information on historical worldwide trades. And, third, the data at the Deutsche Bundesbank allows to robustly measure impacts across financial markets, since we

[2]Gehde-Trapp et al. (2015) mention that "*The DTCC estimates that its coverage of* (the TIW database on) *credit derivatives amounts to 95% of single-name CDS in terms of the number of contracts, and 99% of single-name CDS with respect to notional amounts*"

[3]Moreover, CDS spreads are an important credit risk indicator, and existing literature has established that CDSs lead bond and equity prices (Acharya and Johnson 2007; Blanco et al. 2005; Longstaff et al. 2005)

have access to detailed, investor-level holdings of credit derivatives, bonds, and equity.

The empirical analysis starts with the study of the new equilibrium in the German CDS market, after the dealer's exit. We first conduct an analysis on volumes and, second, on traded prices. Using the set of transactions, we collapse the dataset at investor $\times$ reference entity level in order to study whether investors trade *less* notional in CDS references with a relatively *higher* treatment intensity. The specifications are saturated with investor, investor $\times$ country, investor $\times$ industry, and investor $\times$ rating score fixed effects.

The challenge when interpreting the volume results is to disentangle the supply of CDS liquidity - affected by the exit of the large bank - from confounding trends at the level of investor demand. While part of this concern is mitigated by including investor fixed effects, it could still be possible that German investors reduce faster their demand for the reference entities treated with higher intensity. We take two steps to alleviate this potential problem. First, we show that the top three German dealers hold similar inventories as the rest of the market. This establishes that the treatment intensity is not particularly correlated to the risk of the underlying. And second, we study the behaviour of traded CDS prices. If this was indeed a shock to the supply of CDS liquidity, then we should observe an increase in transaction prices, along with the decrease in volumes. On the contrary, if the observed reductions in volume had been driven by weaker investor demand, prices should also decrease.

We study price effects by looking at changes in the bid-ask spreads on the CDS upfront payments. Most CDS contracts trade with standardized notionals, maturities, and fixed coupons.[4] The buyer and the dealer exchange upfront payments at the start of the contract, in order to compensate for the discrepancy between the fixed coupon, which reflects the regular protection payment, and the actual price of protection agreed upon at the time of entering the contract. Our data

[4]Since the implementation of the Big Bang and the Small Bang protocols in 2009, the contracts have been trading on standardized terms. The notional amount is typically 5 million, there are four maturity dates in a year, known as the IMM dates - on the 20th of March, June, September and, respectively, December - and typically one of the two coupons: 100bps or 500bps, depending on the risk of the underlying.

includes both the actual traded upfront payments, and the corresponding upfront quotes from Markit.

We measure the price impact of the liquidity shock by studying the discrepancy between the traded and the quoted upfront fees, *for a contract with the same characteristics, traded on the same day.*[5] The advantage of using this pricing measure is that it is robust to within-day changes in publicly available information on the reference entity and also to changes in the composition of contract types across the period of analysis. We then estimate panel difference-in-differences models on the realized bid-ask spreads across all new transactions entered into by German banks between January 2014 and June 2015. In the most restricted specification, we add investor × month fixed effects to account for time-variant, investor-specific pricing biases.

Lastly, our analysis turns to the bond market, as we investigate the effects of the CDS market shock on bond spreads. We collect all live bonds issued by firms with CDS traded on them and we study how the yield to maturity varies with our measure of treatment intensity. The model employed is a monthly difference-in-differences panel on the logarithm of the yield, with bond and month fixed effects, as well as same-day macro indicators. We also study the interaction between our treatment measure and a linear function of the rating scores, in order to see how the estimate varies with the riskiness of the bond. Finally, we augment the analysis with one crucial step - detailed investor holdings -, in order to strengthen causality and provide further evidence on the mechanism driving the results.

Using investor-level bond portfolios, we estimate models explaining the rate of growth of holdings at investor × bond level, by treating the bonds on which the investor was long or short CDS protection, in the pre-period. In order to make sure that we capture the effect of CDS frictions and not any confounders that affect differentially CDS-traded and non CDS-traded bonds, we include an indicator for all those bonds issued by firms with CDS traded globally. The advantage of this analysis is that we can study changes in individual demand for the bonds to which

[5]Effectively, this means that we study changes in the half bid-ask spreads - calculated as the difference between the traded bid or ask upfront (depending on the direction of the contract) and the quoted upfront mid.

investors were also exposed in the CDS market.

The estimations on the CDS market reveal that German banks decrease their CDS traded volumes after the liquidity shock. The decrease is proportional to the dealer's market share: when treatment intensity increases by 10pp the same investor decreases the CDS exposure to the treated entity by 13pp more relative to their CDS exposures to the remaining reference entities. We also document an increase in the the bid-ask spreads on the upfront CDS payments, confirming that this is indeed a shock to the supply of CDS liquidity. Precisely, the transaction costs on a round-trade CDS contract increase by 0.10 percentage points, which is equivalent to 7.4% of the total upfront fee. To trade standard CDS contracts of EUR 5 mln notional and with a five year maturity, buyers have to pay upfront EUR 5,000 more on transaction costs, on average.

Lastly, we find that the effects spill over to bond yields and bond holdings. A 10pp increase in treatment intensity raises bond yields by 6 basis points on average. German banks rebalance their bond portfolios, especially if they had previously purchased CDS protection. The effects are strongest in the riskiest buckets, from lower medium investment grade to speculative and below.

We contribute to the literature in three ways. First, we add to recent studies on the *role of CDS markets*. We provide evidence of a positive function of CDS markets in terms of reducing bond spreads and subsequently firms' cost of capital. In this sense, we confirm the descriptive findings in Oehmke and Zawadowski (2016) that investors use the CDS market for hedging - with CDS and bond volumes increasing proportionately. Gündüz et al. (2017) and Saretto and Tookes (2013) also document the positive role of CDSs. Gündüz et al. (2017) show that following a liquidity improvement in the European CDS market as a result of the Small Bang protocol, German banks increased their credit exposures to firms. Saretto and Tookes (2013) show that lenders appear more willing to extend credit to firms with traded CDS and that this behaviour is more pronounced in the presence of capital constraints. In earlier work, Ashcraft and Santos (2009) compared firms with and without CDS trading and found no effect on bond or loan spreads for the average firm. Most of the remaining literature has focused on the harmful effects of CDSs. Subrahmanyam et al. (2014) find that, after the inception of CDS trading, the probabilities of credit rating downgrades or of bankruptcy increase substantially. They argue that this is due to the effect of 'empty creditors' or disinterested lenders that retain control rights but not the economic exposures to the underlying firms. In the same spirit, Amiram et al. (2017) show that the onset of CDS trading on a firm's debt increases the share of loans retained by the loan syndicate lead arrangers, in order to reinforce their commitment to monitoring.

Second, we extend previous research on the *structure and externalities of OTC markets*. Biais (1993) provides the workhorse theoretical model to compare opaque and exchange markets. Pagano and Röell (1996), De Frutos and Manzano (2002), Duffie et al. (2005), and Yin (2005) use this framework to introduce imperfections due to adverse selection, generalized risk aversion, and search frictions. More recent literature has showed that these characteristics of the OTC markets result in core-periphery networks, in which most of the trading is intermediated by a few dealers (Atkeson et al. 2015; Babus and Kondor 2018; Li and Schürhoff 2019). In this context, it becomes crucial to understand how changes in the number of liquidity suppliers impact the functioning of the OTC market.

Di Maggio et al. (2017) find that following the collapse of a dealer in bond markets, intermediation chains between buyers and sellers lengthen significantly, resulting in higher costs for clients looking for liquidity. Similarly, Eisfeldt et al. (2018) find that the failure of a CDS dealer with large risk bearing capacity increases spreads by 40%. Siriwardane (2019) shows that capital fluctuations of large CDS dealers affect the prices of CDSs. Unlike Di Maggio et al. (2017) and Eisfeldt et al. (2018) we study the impact of a liquidity shock driven by a reduction in the number of dealers in the CDS market, how it affects equilibrium traded prices and volumes, as well as its spillover effects. The implications are likely different, since the increase in spreads we document is purely driven by a negative shock to liquidity supply, and not by contagion or counterparty risk considerations.

Our third contribution is to the recent literature that has studied the *effects of regulation on market making*. Duffie (2012) argues that regulatory provisions that penalise risk taking in dealer inventories can lead to substantial decreases in the quality and quantity of market making, as well as to the exit of some dealers. This could increase trading costs for investors, reduce the resilience of markets, lower the quality of information revealed through security prices, and drive up the cost of capital for corporations and governments. A few early papers found that anticipating post-crisis regulations had no negative effect on dealer liquidity (Trebbi and Xiao 2017; Bessembinder et al. 2018; Anderson and Stulz 2017). However, Bao et al. (2018) show that liquidity provision in US bonds decreased following the implementation of the Volker Rule, and in particular around bond downgrades. Adrian et al. (2017) find that prior to the financial crisis, bonds traded by more levered institutions and institutions with investment bank like characteristics were more liquid, and that this relationship reverses after the financial crisis. We add to this literature by showing that when regulatory provisions affect the liquidity of derivative markets, there can be spillovers to underlying securities, and real effects.

The reminder of the paper is organized as follows. Section II is dedicated to the analysis of the CDS market. We introduce the research design, the CDS data, the empirical strategy, and we review the results. Section III turns to the bond market, and the analysis of real effects. We first present the data and the analysis on bond yields, after which we study whether investors rebalance their bond portfolios in response to the shock. Finally, Section IV reports the conclusions of this study.

2 Consequences of the Liquidity Shock for the CDS Market

In this section, we study how the CDS market reacts to a plausibly exogenous reduction in the number of dealers providing liquidity. We do so by analysing the effects of the shock in the cross-section of CDS-traded reference entities. Under the null hypothesis of a perfectly competitive market and free flowing capital, there should be no effect on equilibrium traded quantities and prices.Profitable trades at firm level should be met with liquidity supply from the remaining dealers, or from new market entrants. Alternatively, the reduction in the number of dealers could lead to a decrease in liquidity, with lower traded volumes and higher prices.

This occurs if there are barriers to capital flows, as well as barriers to entry. In subsection 2.1, we outline the main the features of the CDS market. Subsection 2.2 reviews the academic and the policy-based knowledge about the structure of the OTC markets. Theoretical models as well as institutional factors both explain why there could be substantial frictions in this market, leading to deviations from the null hypothesis (Duffie et al. 2005; Duffie 2010). Subsection 2.3 sets out the research design. The reduction in the number of CDS liquidity suppliers at product level - on single-name CDSs - provides the necessary shock, exogenous to individual reference entities. Detailed fixed effects ensure that we remove confounders. Subsection 2.4 describes our data laboratory: the German CDS market. Finally, in Subsection 2.5 we present the analysis and the results.

2.1 The CDS Market: Overview

A credit default swap is a financial derivative that is used to hedge against default by a certain underlying entity. It is traded on the OTC market, for hedging but also for credit risk speculation or arbitrage, and it is in zero net supply. The underlying can be a firm or a sovereign (in which case it is a "single-name CDS"), or a index of securities (or a multi-name CDS). In a typical CDS contract, a CDS protection buyer purchases credit insurance from a CDS protection seller, for a standardized amount, with a pre-set maturity date (at one of the four IMM dates), and in exchange for a fixed coupon, in general of 100 or 500 bps. At transaction date, the buyer and the seller exchange the upfront payment, which is the net present value of the difference between the market coupon and the fixed coupon of the contract. Therefore, all variation in traded CDS prices is comprised in the upfront payments.

Even though outstanding CDS notionals have declined since the financial crisis, the product is still highly traded. At the end of December 2013, there were \$11 trillion single-name CDSs outstanding, and close to \$9 trillion multi-name CDSs.[6] This is almost as much as the outstanding volume of the bond market, which was of \$23 trillion at the end of the same year. Figure 6 in the online appendix shows

[6]Refer to BIS Statistics, at: https://www.bis.org/publ/qtrpdf

the evolution of the two market segments since 2005.

2.2 The CDS Market: Theoretical and Institutional Aspects

This subsection reviews some of the existing knowledge on the structure of the CDS market. Our motivation is to use this knowledge in order to derive testable hypotheses about the effect that a reduction in the number of dealers could have on the CDS market equilibrium. Subsequently, we conduct empirical tests to test these hypotheses.

CDSs are traded on the OTC market, which is naturally opaque and prone to concentrated market structures. In these markets, search frictions are high. Moreover, the costs of operating in an OTC market are large, because dealers typically hold large inventories. This implies that barriers to entry are also high, in particular for smaller firms. Search frictions and barriers to entry can sustain prices that are above competitive levels.

Search frictions are mainly understood as the direct costs investors must incur in order to find a dealer who is willing to trade. But there are also indirect costs, stemming from the fact that dealer quotes are fleeting. Buyside investors need to decide on the spot whether to enter the trade at the firm quote a dealer offers them, or else they incur the risk of being offered a worse price. This prevents investors from fully researching their outside options. It is through these two mechanisms that the existence of search frictions leads to bid-ask spreads which are higher than the competitive level (Duffie et al. 2005).

Barriers to entry imply that is it difficult for external firms to challenge the incumbents, typically due to institutional features. Barriers to entry support concentrated market structures and reinforce the possibility to earn monopolistic rents. In fact, Siriwardane (2019) shows that in the single-name CDS market, 75% of the supply of liquidity is in the hands of five dealers.

Recent literature suggests that it is indeed the case that in OTC markets dealers can extract and maintain bid-ask spreads above competitive levels. Indeed, Green et al. (2006) note that dealers in the municipal bond market exercise substantial market power. In the corporate bond market, Di Maggio et al. (2017) find that, when dealers trade with clients, they change a mark-up that is 50 basis points higher than when they trade with other dealers. For the CDS market, Eisfeldt et al. (2018) find that credit spreads of dealer-to-dealer trades are nearly 6 percent lower than those of dealer-to-customer trades.

In this type of market structures with a finite number of suppliers, any single dealer's supply is likely to impact market clearing prices. Moreover, in response to a reduction in the number of suppliers, the remaining dealers could act strategically when deciding on the equilibrium quantity supplied and the bid-ask spreads they offer. This means that, in addition to accounting for information about asset fundamentals and investor demand, traded prices are fixed as a best response to the supply of other dealers. At the new market equilibrium, this could result in lower traded volumes and higher rents. Theoretical models have formalized this intuition. Bernhardt et al. (2004) show theoretically that, in dealer markets, imperfect competition leads to higher transaction costs for retail trades. They also offer empirical evidence that this was indeed the case for equities on the London Stock Exchange when it functioned as a dealer market. Foucault et al. (2013) show in a simple game theoretic framework that in opaque markets with a finite numbers of dealers, dealers act strategically in order to earn monopoly rents. The lower the number of dealers, the higher the rents. Finally, in this type of markets, relationship trading tends to be important. In fact, Hendershott et al. (2017) study insurer trading patterns in corporate bonds and find that 30% of the insurers trade with a single dealer.

A reduction in the number of suppliers of single-name CDS market liquidity could, therefore, increase the difficulty to trade CDSs through three channels. First, even in the absence of oligopolistic dynamics, it implies a decrease in the overall risk bearing capacity of the CDS liquidity suppliers. Because increasing inventories is costly, absorbing the additional demand that comes from the dealer's clients is going to take time. It is likely that the remaining dealers would only accept to increase their inventories if clients were willing to pay higher prices. Second, the remaining dealers are likely to respond strategically to reductions in the number of suppliers. By reducing the quantity they offer, they could profit from the higher concentration, and increase markups. And, third, the destruction of long-term dealer-customer relationships would have a negative impact on the investors who are forced to switch dealers. These three channels explain why changes in the number of liquidity suppliers could have a price and a volume impact, at least in the short to medium term. In the rest of the section we test the null hypothesis of no effect - perfect capital markets -, versus the alternative hypothesis - institutional frictions generate a price and liquidity impact.

2.3 Research Design

To generate quasi-experimental variation in the supply of CDS market liquidity at reference entity level, we exploit a reduction in the number of dealers which occurs for reasons unrelated both to the underlying risk of the reference entities and to investor demand. On 13 November 2014, one major dealer headquartered in Germany announces its decision to exit market making in single-name CDSs. This decision is part of a broader shift in strategy aimed at achieving higher capital savings. Consistent with a supply shock, we show that this decision is not driven by either investor trends, nor by the riskiness of the underlying reference entities. The empirical analysis uses as a main explanatory variable the ex-ante intensity of trading in CDS by the exiting dealer, at a reference entity. We do this in a series of difference-in-difference analyses where the treatment intensity varies in the cross-section of firms. In order to take into account the possibility of any leaked information prior to the announcement, the analysis employs October 1, 2014 as a threshold separating the pre-treatment from the post-treatment period.[7]

Because the single-name CDS market has experienced a slower penetration of clearing than other derivative products, the derivative became very expensive in terms of capital requirements in light of recent changes in capital regulations. This was especially relevant as dealers prepared to adapt to the leverage ratio. Generally, the leverage ratio applies to net dealer inventories. However, in the

[7] We note however that a dealer has all the incentives to avoid revealing its intentions to leave a market prematurely, in order to prevent becoming exposed to predatory trading (Barbon, Di Maggio, Franzoni, and Landier Barbon et al.).

case of single-name CDS, dealers had to provision capital proportionally to gross inventories. Therefore, exiting market making in single-name CDSs could have provided an important source of capital savings. Below, we offer more context on this issue.

In recent years, increases in the capital requirements of bank-affiliated dealers have drained liquidity from over-the-counter markets, especially for products that occupy a lot of space on dealer balance sheets, such as bonds, swaps, repos and foreign exchange contracts. Dealers have reduced their market-making inventories and are offering less liquid two-way markets for asset classes whose capital requirements have increased significantly. For example, under the US supplementary leverage ratio rule for the largest US broker-dealers, every $100 million of additional assets requires an additional $5 million of capital, regardless of the risk of the assets. This means that intermediating safe assets requires a lot of capital relative to the tiny risk involved.

In general, dealers best respond to higher capital requirements by increasing bid-ask spreads for positions that require a lot of regulatory capital relative to their risk. In fact, there is now evidence that this is indeed the case in practice. Duffie (2017) argues that since the imposition of the supplementary leverage ratio rule, bid-ask spreads in the US Treasury repo market have increased from around 3 basis points to more than 16bp. Siriwardane (2019) shows that $1 billion reduction in dealer capital leads to an increase of 3bps in CDS spreads. A second response of the dealers to these regulations has been to use financial engineering or new intermediation methodologies to economise on the use of balance sheet space. These methods include clearing and compression, which allow dealers to net buy and sell positions and only report capital on the net amount outstanding.

Market making in CDSs has been indeed affected by the same trends. One particularity of the single-name segment, however, is the fact that clearing has been very slow to penetrate this market. According to BIS Statistics, at the end of December 2013, less than 20% of single-name CDSs had been subject to clearing (see Figure 7 in the Online Appendix). In the absence of clearing, dealers cannot net their CDS positions and the leverage amount is applied on the entire market making inventory. As a result, single-name CDSs are particularly costly for dealers to intermediate in terms of capital regulation.

The German buyside market represents a very small fraction of the overall CDS market (just under 2% in terms of gross notional traded in the single-name segment), which implies that the analysis is not vulnerable to reverse causality (i.e., changes in investor behaviour at home could not have caused the exit of the dealer). Moreover, Figure 3 also shows that the risk profile of the three market-makers headquartered in Germany is very similar to the overall risk-profile of the CDS market. However, the robustness of the treatment measure remains vulnerable to omitted variable bias. We will take steps to mitigate these concerns throughout the analysis by including specifications with detailed investor-level fixed effects.

2.4 CDS Data Laboratory

The analysis of the CDS market equilibrium relies on CDS transaction and position data from the Depository Trust and Clearing Corporation (DTCC). The Deutsche Bundesbank receives from DTCC all trades of CDS contracts - the flow -, and all CDS positions - the stock - if at least one trading counterparty is a German bank or, alternatively, if the reference entity on which the CDS is traded is headquartered in Germany. For the purpose of this analysis, we work with the former dataset: the trades and holdings of German banks.

The CDS position or stock data is crucial to calculating the measure of treatment intensity that is used to investigate the effect of the supply shock. This data contains weekly CDS gross sell and buy notional volumes outstanding, by reference entity, party, and counterparty to the trade. This includes the complete positions of the exiting dealer, which we aggregate across counterparty, at dealer and reference entity level. We then calculate the average market shares of the dealer by reference entity, by combining this data with the global aggregated volumes that DTCC provides to subscribers on the top 1,000 CDS-traded reference entitites. This latter dataset is the one used by Oehmke and Zawadowski (2016).

To measure the price and volume effects on buyside investors we use the CDS transaction or flow dataset. We apply the following cleaning procedures. From the overall dataset, we first select transactions that represent risk-taking (these are new trades, assignments of existing trades to third counterparties, and trade terminations). Because we investigate the effects on final customers which in this market are the buyside investors, we extract dealer-to-buyside transactions. We therefore exclude the inter-dealer market.[8] Our sample thus includes all the buyside trades of German investors excluding those realised by the exiting dealer. Over the period January 2012 to May 2015, we have 843,645 buyside entries.

Next, we select standardized contracts, which are contracts that follow the definitions set in the Big Bang and Small Bang protocols. Standard contracts are fairly homogeneous, they trade under fixed legal definitions, with pre-set maturities, amounts, and fixed protection coupons of typically 100bps or 500bps. Because the coupons are fixed, the price of this contract is exchanged upfront, and it amounts to the discounted value of the difference between the market value of the coupon and the fixed rate. When the seller of CDS protection estimates the value of the protection coupon to be higher than the market value, the protection buyer makes an upfront payment to the protection seller. Conversely, when the dealer estimates that the fixed coupon is too high a price for protection, the CDS protection buyer receives an upfront payment from the seller. Therefore, all price variation is comprised in the upfront spread.

We identify new standard trades following these three steps: (1) we keep new trades and assignments reported by the new party entering the trade, and we thus exclude trade terminations (44% of sample), and assignments reported by the party exiting the trade (12% of sample); (2) we only keep the new trades and assignments for which there is information on the upfront spreads (we drop 22% of sample); and (3) we keep only contracts for which the ISDA definition matrix includes the term "Standard" (we drop 0.5% of sample). Finally, in order to merge with the treatment measure calculated based on the position data, we only keep trades done on the top 1,000 CDS-traded reference entities (with this point, we exclude an additional 14% of the sample).

[8]There are two main reasons why we choose to investigate the buyside market. First, final investors are the main consumers in this market and any price of volume effects are likely to negatively impact their welfare. And, second, while we can measure the effects on German investors as a whole, from Germany we observe only a segment of the inter-dealer market.

Our extended period of analysis thus spans from January 2012 to June 2015, and it covers 118,411 buyside-to-dealer transactions for which the buyside party is a German bank, and the counterparty is a German or international dealer. The dataset contains relevant contract and reference entity characteristics including traded notionals, prices, the direction of the trades (buy or sell), the currency of the trade, its maturity, the identity of the trading parties as well as the sector, type and identity of the reference entity.

Most of the empirical analysis is focused on the period January 2014 to June 2015.[9] Over this period, we collected 47,923 trades entered into by 43 banks, on 780 reference entities. This is the final dataset that we use in the volume analysis. For the price analysis, we augment the dataset by adding the Markit upfront quotes to each trade, and we match these both on trade day and on contract characteristics. We thus collect matching upfront quotes for 17,544 trades.

Table 1 presents summary statistics on the main characteristics of the CDS trades, measured in the pre-period. Close to half of the transactions concern non-financial firms, while the remaining half is comprised of financial institutions and sovereigns. 52% of the trades are to buy CDS protection, while 48% are to sell protection. The average maturity of the traded contract is around 5 years, and the average amount traded is close to 5 million. The average upfront spread paid on a contract is 1.34% of gross notional, out of which 0.04% are the transaction costs, or the half of the bid-ask spread.

[9]The dynamic analysis with time trends relies on longer panels and spans between January 2012 to June 2015.

Table 1: . Summary Statistics: CDS Transactions

	N (1)	Mean (2)	SD (3)	P10 (4)	P50 (5)	P90 (6)
CDS Volume Analysis						
Notional (EUR 000,000)	47,923	4.95	6.87	0.38	3.63	10.50
Fixed Rate	47,923	2.07	1.75	1	1	5
Buyside Trade Indicator	47,923	0.52	0.49	0	1	1
Maturity (in years)	47,923	4.27	1.78	2	5	5
Rating Score	47,923	10.62	5.06	5	9	19
CDS Price Analysis						
Upfront Price (in %)	17,544	1.35	15.41	-12.13	-1.07	13.12
Half Spread (in %)	17,544	0.04	0.05	0.00	0.01	0.11
Distribution by Sector of CDS Holdings						
- non-financial reference entities	21,338	44.57 %				
- financial reference entities	14,078	29.40 %				
- sovereign reference entities	12,462	26.03 %				

This table reports summary statistics for the main variables employed in the analysis over the pre-period, that is, from January to September 2014.

2.5 Analysis and Results

This section describes the empirical methods used to study the transition of the CDS market to a new equilibrium, following the liquidity shock. For this, we study effects on both the likelihood of trading CDS and on the total volumes traded by the German buyside investors, as well as the prices they pay when they enter CDS trades. We begin by introducing below our measure of treatment intensity. Then we discuss possible identification concerns as well as the steps we take to mitigate them.

2.5.1 Constructing the Heterogeneous Treatment Variable

The main explanatory variable employed in the analysis captures intensity of treatment by means of the the share of CDS notional intermediated by the exiting dealer, at reference entity level. For this, we combine the information in the individual positions data with the gross notional information provided by DTCC, and we calculate the average market share of the dealer for each of the 1,000 CDS traded reference entities covered by our. To ensure the stability of the measure, we use the average market share over the three years prior to the dealer's decision to exit.

Therefore, for each of the top 1,000 reference entities on which we have information, this ratio is as follows:

$$TreatmentIntensity_f = \frac{DealerGrossNotional_f}{TotalGrossNotional_f}$$

With this measure, we investigate the impact of the CDS supply shock on the liquidity offered to German buyside investors across reference entities treated heterogeneously.

2.5.2 Identification Challenges

There are two important identification challenges that affect the analysis of the CDS market. The first challenge is to disentangle the supply of CDS liquidity - shocked by the reduction in the number of dealers - from confounding trends at the level of investor demand. The second challenge is to account for any possible correlation between the market share of the exiting dealer and the characteristics (and in particular the risk profile) of traded reference entities. We explain below how we tackle these two challenges.

We take several steps in order to be confident that we separate supply and demand in the CDS market. We start by plotting the monthly volume of CDS new trading by German buyside investors, from July 2013 to June 2015. While we observe some recurrent patterns in fluctuations, especially around IMM dates, it appears at a first glance that there is a marked decrease in volume of new trading coinciding with the supply shock to CDS liquidity.

Figure 1 shows the aggregated new trades purchased by the 43 German buyside banks. The underlying data is sourced from DTCC.

We further decompose this decrease, by studying the composition of new trades in Figure 2. In particular, we track the share of new trades that are done on reference entities that are highly treated, as a percentage of total. We consider that highly treated reference entities are those with an exposure to the treatment above the median. While prior to October 2014, roughly 50% of the trades were done on highly treated reference entities, over the six months following the exit

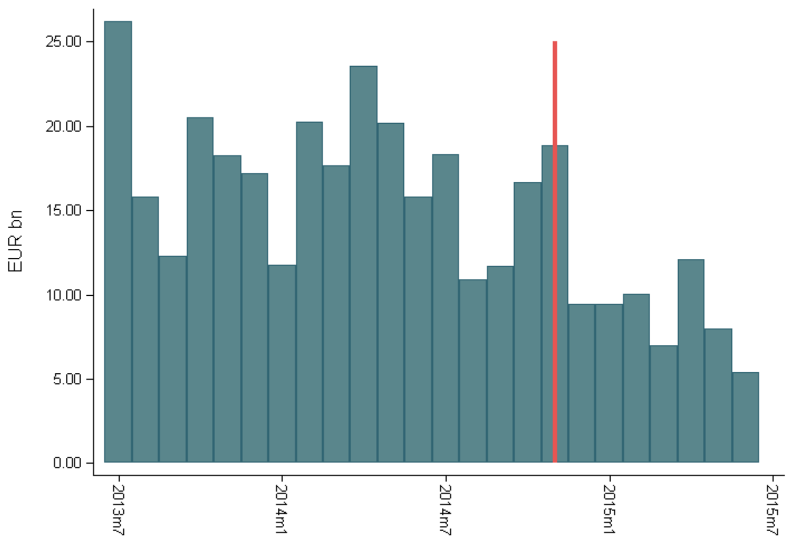

Figure 1: . Total Trading in Single-Name CDS Contracts by the German Buyside

their share in total new trades falls to around 30%. This forensic analysis is consistent with a shock to the supply of CDS liquidity, affecting reference entities proportionally to their ex-ante exposure to the dealer.

Another important tool that allows us to separate the estimation of supply and demand effects is including a set of fixed effects at investor level. While the evidence presented above suggests that there is a decrease in CDS trading that coincides with the supply shock, it could still be possible that German investors reduce faster their demand for the reference entities treated with higher intensity. Investor fixed effects help us alleviate this problem. In particular, by including investor fixed effects in our estimations, we effectively estimate the effect of the supply shock for highly treated reference entities versus lowly treated ones, for the same investor, and at the same time. What still remains is the possibility that German investors start reducing their demand for certain segments of the CDS market (maybe the riskiest or the safest reference entities, or exposures to certain industries or geographical areas), and that this occurs concurrently with the exit of the dealer. To mitigate these concerns, we further include in our specifications investor $\times$ country, investor $\times$ industry, and investor $\times$ rating score fixed effects.

And, finally, we can confirm the supply shock because we observe full market

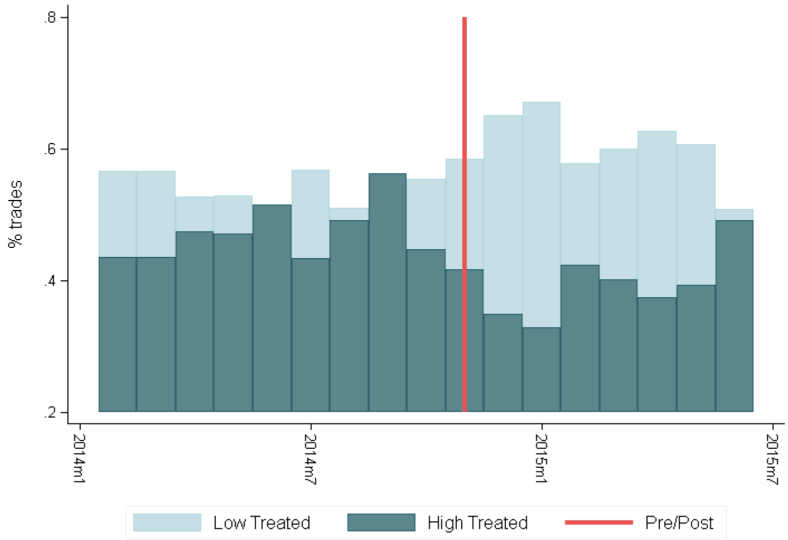

Figure 2: . High-Treated and Low-Treated Contracts in Total

Figure 2 shows the evolution of the share of high-treated CDS contracts versus low-treated contracts in the total new CDS trades done by German buyside investors. The underlying data is sourced from DTCC.

outcomes: volumes and prices. If demand frictions prevailed, we should observe the CDS market converging to an equilibrium with lower traded volumes and prices. If however, supply frictions drive equilibrium outcomes, then at the new equilibrium there would be lower traded volumes, but higher prices. In addition, because we can use the heterogeneous worldwide market shares of the exiting dealer, we can test whether any changes in volume and prices are directly proportional to these market shares.

The second identification challenge requires us to understand whether there is any pattern of correlation between our treatment intensity variable and the characteristics of the reference entities. Because CDS contracts are used to trade credit risk, the most important characteristic that we are concern with is the riskiness of the underlying. We take two steps to alleviate any potential risk correlations. First, we include in all of our regressions a linear function of the rating scores provided by the three main rating agencies (S&P, Fitch and Moody's), as well as the interaction between the score and explanatory variables in some specifications. And second, we show that the top three German dealers hold inventories that are similarly distributed in terms of risk as the overall CDS market. Figure 3 plots the distribution of the total CDS notional traded by German dealers by risk buckets (in red) and the same distribution for the overall CDS market based on the DTCC totals (in white), as well as for the German buyside (in blue).

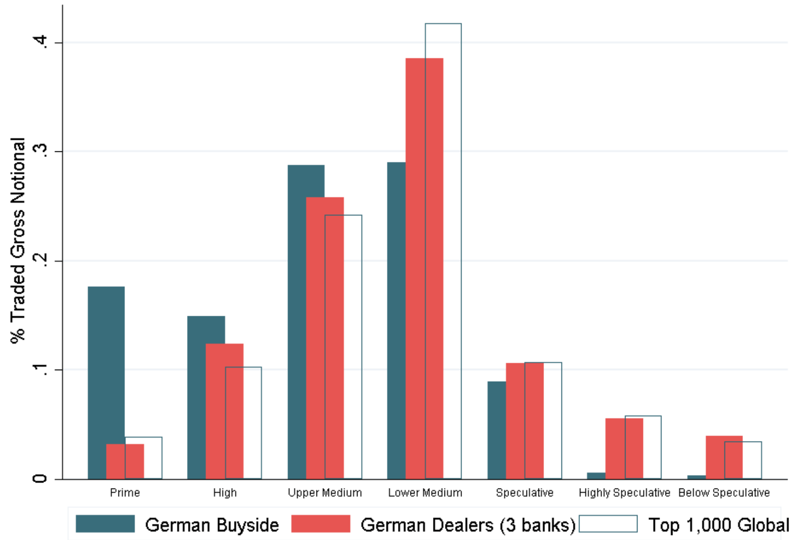

Figure 3: . Risk Distribution of CDS Traded Volumes

This figure shows the distribution of gross notional on the top 1,000 CDS reference entities across rating buckets for three groups: total world notional, total gross notional of the top three German dealers, and total notional of the German buyside. The data underlying the figure comes from DTCC and Bloomberg.

Below, we describe the different steps of the empirical analysis on the CDS volumes and prices.

2.5.3 Analysis of CDS Volumes

We start the analysis by studying the effects of the treatment on the probability to trade CDS contracts, over the longer term horizon, from January 2012 until June 2015. For this, we build a quarterly balanced panel at investor $\times$ reference entity $\times$ quarter. We then run a linear probability model as a baseline specification:

$$\begin{aligned} ProbaNewTrade_{ift} =& TreatmentIntensity_f * Post_t + TreatmentIntensity_f \\ &+ Post_t + \epsilon_{ift} \end{aligned} \tag{1}$$

where f stands for the reference firm, i stands for the investor and t stands for quarter.

The explained variable $ProbaNewTrade_{bft}$ takes value 1 in quarters when there is at least one new trade of a buyside investor on a reference entity, and it takes value 0 in quarters without any trades. The regression is a standard difference-in-differences with heterogeneous treatment, where the variable $Post_t$ takes value 1 from the forth quarter of 2014 onwards. This choice is justified by running the specification dynamically in order to observe when the effect kicks in.

We enrich the baseline specification with a wide set of fixed effects and firm characteristics, in order to eliminate any confounding factors. We first saturate the model with investor and investor $\times$ quarter fixed effects, in order to control for time-varying, unobserved investor demand. Adding these fixed effects mitigates unobserved variables at investor level, such as changes in their investment strategy. Therefore, we study whether, for the same investor and the same quarter, the probability of entering a new trade on a CDS-traded reference entity is inversely proportional to the dealer market share in the three quarters following the exit. Second, we augment the model with control for firm characteristics, such as sector, industry, country and ratings.

We also estimate models with time trends at several levels: investor, investor $\times$ sector, investor $\times$ country and investor $\times$ rating bucket. This is to ensure that any volume effects observed are unrelated to pre-existing investor-level trading strategies aimed at cutting exposures to specific industries, countries or risk levels. Finally, we separate the sample in trades where investors are buying protection and trades where they are selling protection.

To quantify the volume effects, we continue by employing standard pre-post difference-in-differences specification, on the shorter horizon of analysis: January 2014 to June 2015. For this, we first collapse our initial dataset of 47,923 transactions at investor $\times$ reference level, and we build a balanced panel. Each observation then captures the total notional in new trades that an investor contracted on a certain reference entity in the pre-treatment, or in the post-treatment period. With this, we then calculate how the rate of growth of CDS notional at investor and reference level varies with the treatment intensity variable. This model is equivalent to including investor $\times$ reference fixed effects, and it is robust to serial correlation.

Our final panel includes the rates of growth of CDS exposures for 4,944 investor $\times$ reference entity pairs. This implies that, on average, a German bank has new CDS exposures to 116 reference entities. The baseline model is the following:

$$DeltaVolume_{i,f,pre-post} = TreatmentIntensity_{f,pre} + \epsilon_{i,f,pre-post} \tag{2}$$

To estimate overall changes between the pre and post periods, we first employ as dependent variable a measure of changes in overall CDS notional, defined as follows:

$$DeltaVolume_{f,i,pre-post} = \frac{(CDSNotional_{f,i,post} - CDSNotional_{f,i,pre})}{0.5(CDSNotional_{f,i,post} + CDSNotional_{f,i,pre})}$$

where f stands for the reference firms and i stands for the investor.

The average of $DeltaVolume_{f,i,pre-post}$ is -0.96, consistent with the decline observed in CDS traded volumes over the period, while its standard deviation is 1.42. The measure is bounded between [-2,2]. In order to ensure that our results are not driven by unobservable trends, we include in the regression controls for the reference entity (industry, country and rating buckets) as well as, progressively, fixed effects for investor, investor $\times$ industry, investor $\times$ country, and investor $\times$ rating bucket. We cluster standard errors at reference entity level - the level at which treatment is applied.

In addition, we then also study dependent variables that capture the extensive margin: new contracts and contract terminations. To study the effect on new contracts, we create a dummy variable that takes value 1 when the average notional at investor $\times$ contract level is positive in the post period and zero in the pre period. To study the effect on contract terminations, we create a second dummy variable that takes value 1 when the average notional at investor $\times$ contract level is zero in the post period and positive in the pre period. As above, we saturate the model with with fixed effects for ratings, country and industry, and we separate the analysis for buy and sell trades. Finally, we look at the effects by type of reference entities: corporate non financial, corporate financial, and sovereigns.

2.5.4 Analysis of CDS Prices

This section sets out our empirical study of CDS prices. In particular, we analyse how changes in the transaction costs incurred on every CDS trade (measured as the half spread with respect to the Markit quote) vary with the measure of treatment intensity. Most CDS contracts trade with standardized notionals, maturities, and fixed coupons.[10] The buyer and the dealer exchange upfront payments at the start of the contract, in order to compensate for the discrepancy between the fixed coupon, which reflects the regular protection payment, and the actual price of protection agreed upon at the time of entering the contract. Our data includes both the actual traded upfront payments, and the corresponding upfront fees from Markit, quoted by the dealers on the different types of standardized contracts.

While any declines in traded volumes could be consistent with both decreases in the supply of CDS liquidity and with declines in investor demand, an analysis of prices sheds light on which of the two alternative explanations prevails. To analyse the effect on the realized CDS spreads, we start with our initial dataset of transactions entered into by the remaining German banks. For each trade, we have the upfront payment, which captures all the variation in the price of the contract. In this part of the analysis, we will focus on the realized spreads, defined as the difference between the bid or the ask upfront prices and a benchmark mid upfront price. Because the (German) CDS market is not sufficiently liquid in order to allow us to estimate mid prices directly from daily prices, we use daily quoted mid upfronts sourced from Markit.

We therefore define the absolute half spread on a CDS contract traded on reference entity f entered at time t as follows:

[10] Since the implementation of the Big Bang and the Small Bang protocols in 2010, the contracts have been trading on standardized terms. The notional amount is typically 5 million, there are four maturity dates in a year, known as the IMM dates - on the 20th of March, June, September and, respectively, December - and typically one of the two coupons: 100bps or 500bps, depending on the risk of the underlying

$$
\begin{aligned}
|HalfSpread_{ft,s}|=&(UpfrontAsk_{ft} - UpfrontMid_{ft}) * \mathbf{1}[s \in selltrade] \\
&- (UpfrontBid_{ft} - UpfrontMid_{ft}) * \mathbf{1}[s \in buytrade]
\end{aligned}
$$

The $UpfrontAsk_{it}$ and the $UpfrontBid_{it}$ are the realised transaction prices. The $UpfrontMid_{it}$ is the daily Markit indicative dealer mid quote, and s is the direction of the trade.

Next, we study the effects of the liquidity shock on this half spread. For this, we run difference in differences specifications on the panel of transactions, at contract level:

$$
\begin{aligned}
|HalfSpread_{cit}|=&TreatmentIntensity_f * Post_t + Firm_f + Month_t \\
&+ \sum_k \gamma_k * \mathbf{1}[currency_j \in k] + \sum_l \gamma_l * \mathbf{1}[maturity_j \in l] \\
&+ \sum_p \gamma_p * \mathbf{1}[rate_j \in p] + \epsilon_{cit}
\end{aligned} \tag{3}
$$

In this model, the dependent variable, $|HalfSpread_{idft}|$, captures the absolute value of the realized half spread on contract c, sold by dealer d, on reference entity f, at time t. The specification controls non-parametrically for contract characteristics in order to take into account changes in the composition of the trades. α_f are reference entity fixed effects. Since CDS contracts mostly trade with standardized maturities and fixed rates, the term $\sum_k \gamma_k * \mathbf{1}[maturity_i \in k]$ includes a full set of dummies for standardized CDS maturities, while the term $\sum_p \gamma p * \mathbf{1}[rate_i \in p]$ includes dummies for standardized fixed rates. $\sum_k \gamma k * \mathbf{1}[rate_i \in k]$ includes dummies for standardized currencies.

Crucially, because we work with deviations from the upfront fees quoted by Markit dealers for the same contract, on the same day, our measure of pricing impact is robust with respect to daily changes in characteristics and risk profile of the underlying entities. Moreveor, in some specifications, we control for market volatility, CDS trading activity and risk free rates by including the VIX, the CDX and CDX high yield indices, as well as the USD and EUR swap rates with maturities of 1, 5 and 10 years. We add reference entity, investor, and month fixed effects, as well as contract characteristics. In the most restricted specification, we add investor × month fixed effects to account for time-variant, investor-specific pricing biases. Finally, we separate the analysis for buy and sell trades.

2.5.5 Results

Our first set of results show that the liquidity shock had a significant and persistent economic impact on the CDS market. Table 8 and Table 9 in the online appendix show that the probability that a buyside investor trades a CDS contract decreases significantly in the post period, and this decrease is inversely related to the treatment intensity. The effect is not only robust to including investor and quarter fixed effects, but it remains strong and significant when the treatment intensity is horseraced with time trends at the level of investor × industry, investor × country and investor × rating. Figure 4 below shows the dynamics of the coefficient on the treatment intensity. These results confirm the fact that the effect kicks in from October 2014, and that it is not driven by pre-exiting investor trends at country, industry or rating bucket.

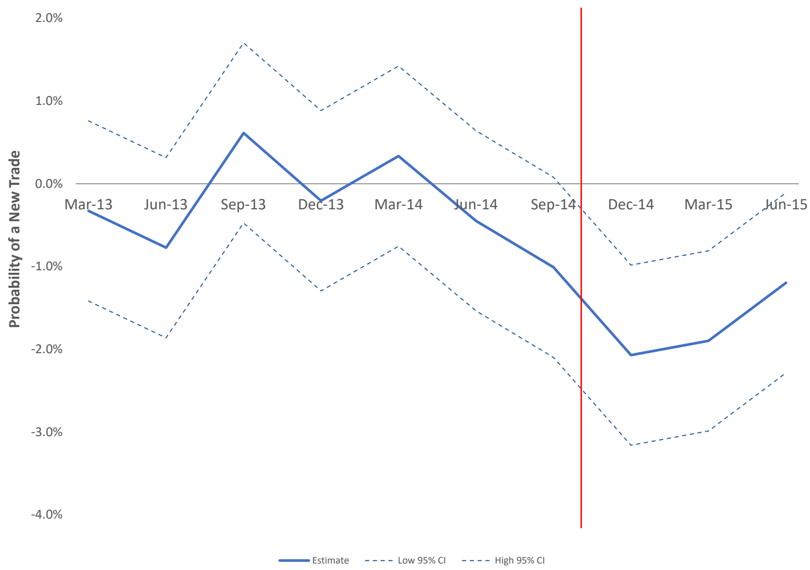

Figure 4: . Dynamic Estimate of the Treatment on the Probability to Trade

This figure shows the dynamic difference-in-differences estimate of effect of the treatment intensity on the probability that an investor enters a new contract on a given reference entity. It is a panel version of the Model (3) in Table 8.

Table 2 presents the results of the volume estimations on the CDS market, following Equation 2. We find that German investors decrease their holdings of CDSs and that the decrease is proportional to the treatment intensity - the exposure to the withdrawing dealer. Because of confidentiality restrictions, we do not evaluate the results at the actual market share, but we employ a 10pp change in the intensity of treatment. Moreover, to facilitate the interpretation, we evaluate the coefficients in the regression tables directly at 10pp.

Table 2: . Effect on CDS Traded Volumes

	Delta Total CDS Notional at Investor X Reference Entity, Pre/Post							
	Delta Notional					Non Financial	Financial	Sovereign
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$TreatmentIntensity$	-0.134**	-0.124**	-0.156***	-0.159***	-0.135***	-0.169***	-0.209**	-0.365
	(0.055)	(0.053)	(0.055)	(0.052)	(0.051)	(0.058)	(0.104)	(0.817)
Reference Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Investor FE	No	Yes	No	No	No	Yes	Yes	Yes
Investor × Industry FE	No	No	Yes	No	No	No	No	No
Investor × Country FE	No	No	No	Yes	No	No	No	No
Investor × Rating FE	No	No	No	Yes	No	No	No	No
Observations	4,944	4,944	4,944	4,944	4,944	2,783	1,631	526
R^2	0.137	0.216	0.308	0.274	0.280	0.240	0.179	0.401

This table reports the coefficients of OLS regressions where the dependent variable is the growth of CDS exposure between the pre-treatment period, January to September 2014, and the post treatment period, October 2014 to June 2015. The independent variable, *TreatmentIntensity* is our measure of treatment heterogeneity and is given by the market share of the dealer calculated for each of the top 1,000 CDS reference entities. The coefficients on the treatment intensity are directly evaluated at a 10pp standard deviation. We start with a simple difference-in-difference estimation in Model (1) and we add investor fixed effects in Model (2). In Models (3) and (4) we explore the effects on the extensive margin, while in Models (5) and (6) we separate the contracts into buy and sell. Standard errors are clustered at reference entity level and reported in brackets, $^{\star}p < 0.10$, $^{\star\star}p < 0.05$, $^{\star\star\star}p < 0.01$

Therefore, a 10pp increase in the treatment intensity leads to a rate of growth lower by 13pp in CDS notional at investor $\times$ reference entity. The coefficient is relatively stable when we include the various fixed effects. Moreover, the effects are strongest for corporate reference entities - both financial and non-financial -, and but also present for sovereigns.

The price analysis further confirms the shock to the supply of CDS liquidity. In the panel specifications presented in Table 3, we find that the bid-ask spreads on the upfront CDS payments increase, signalling an increase in transaction costs consistent with supply frictions. In particular, transaction costs on a round-trip CDS contract increase by 0.10pp (0.056pp for the buyside, and 0.047pp on the sell side), which is equivalent to 7.4% of the average upfront fee. This means that, in order to purchase standard CDS contracts of EUR 5 mln notional, with a five year maturity, buyside investors have to pay an upfront that is on average EUR 5,000 higher than prior to the dealer exit.

Finally, Figure 5 showing the dynamic effect confirms that this increase starts in October 2014 - coinciding with the event - and that it persists for at least four months.

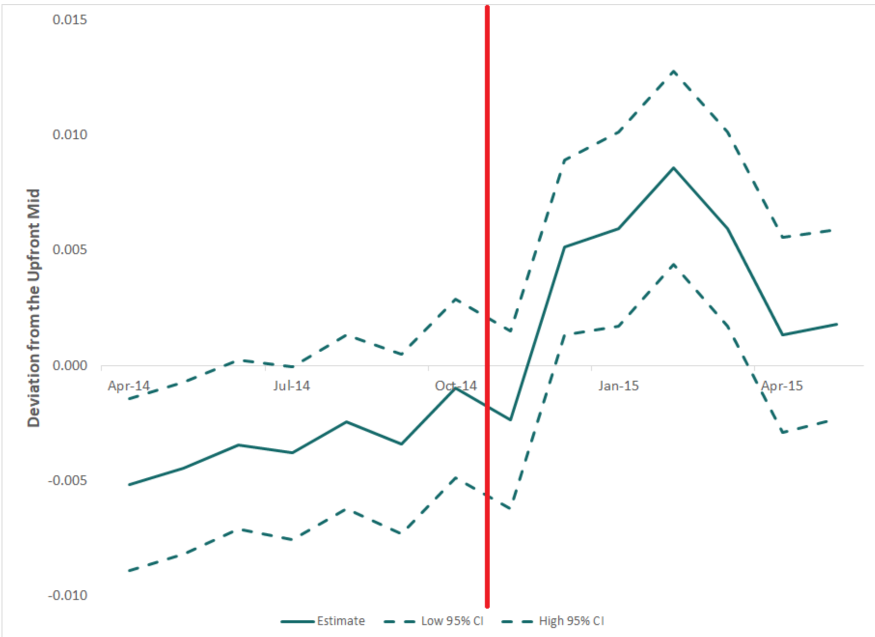

Figure 5: . The Dynamic Estimate of the Treatment on the Bid-Ask Spread

This figure shows the dynamic difference-in-differences estimate of effect of the treatment intensity on the half bid ask spreads at CDS transaction level when treatment intensity increases by 1pp. It is a panel version of the Model (2) in Table 3.

Table 3: . Effect on Traded Bid-Ask Spreads

	Panel Regression on CDS Transactions						
	Half BA Spreads - Absolute Deviations of Traded Upfronts from Quoted Mids						
Sample	All					Buy Trades	Sell Trades
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$TreatmentIntensity \times Post$	0.043**	0.044**	0.052***	0.050***	0.048***	0.056***	0.047***
	(0.020)	(0.020)	(0.018)	(0.018)	(0.018)	(0.009)	(0.008)
$Post$	0.284						
	(0.396)						
Macro Controls	Yes	No	No	No	No	No	No
Contract Characteristics	No	No	Yes	Yes	Yes	Yes	Yes
Reference Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Investor FE	No	No	No	No	Yes	No	No
Month FE	No	Yes	Yes	Yes	No	Yes	Yes
Investor × Month FE	No	No	No	No	Yes	No	No
Observations	17,574	17,544	17,542	17,542	17,502	9,078	8,421
R^2	0.313	0.390	0.397	0.421	0.462	0.419	0.431

This table reports the coefficients of panel OLS regressions explaining the traded prices (upfronts) of CDS contracts. The dependent variable measures the half spread which we calculate as the difference between the traded upfront price and the Markit quoted mid for the same day. The unit of observation is a CDS contract. The analysis runs from January 2014 until June 2015. We estimate difference-in-differences specifications where the pre-period is January to September 2014 and the post-period is October 2014 to June 2015. $TreatmentIntensity$ is the measure of treatment intensity, calculated as the market share of the dealer for each of the 1,000 top CDS reference entities. The coefficients on the treatment intensity are directly evaluated at a 10pp standard deviation. Standard errors are clustered at reference entity and month, and are reported in brackets, $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

3 Spillovers to Corporate Bond Spreads

This section sets out our analysis of the spillover effects of the shock to CDS market liquidity on the corporate bond market. We start with an analysis of bond yields, and then we study whether investors engage in rebalancing of their bond portfolios, in response to the supply shock in CDS. The behaviour of investors will help us understand the channels through which there can be an effect on bond yields.

3.1 Data on Bonds and Investor Securities Holdings

In a first step, we collect data on bond yields. We employ individual bond data extracted from the comprehensive Centralized Securities Database (CSDB). CSDB is a security-by-security database containing monthly data on instruments, issuers and prices for debt securities, equity instruments and investment fund shares issued worldwide. For example, more than 10 million securities were covered only in June 2018. The objective of CSDB is to cover all securities relevant for the analysis carried out by the European System of Central Banks (ESCB). For each live bond we have an entry per month, with the time-variant information referring as of the last day of the month. Relying on a variety of private and public sources, the database includes various time-varying characteristics of the securities, including volumes issued and outstanding, original and residual maturities, yields to maturity, coupon characteristics, as well as information on the country and industry of the issuer. From this database, we extract information on the bonds issued by corporations in the top 1,000 reference entities with traded CDS. To this, we then add ratings information, as well as the treatment variable at issuer level.

In the second step, we study investor bond holdings. For this, we investigate how German banks active in both CDS and bond markets rebalance their portfolios across the two assets, after the CDS liquidity shock. We exploit the Security Holdings Statistics (SHS-Base Plus) Database, also collected by the Deutsche Bundesbank.[11] Financial institutions domiciled in Germany report securities which they hold for domestic or foreign customers. In addition, domestic banks also provide information about their own holdings, irrespective of where the securities are held. The data is collected by means of a full census. The reports include information on debt securities, shares, and investment fund shares or units. The identifier is the International Securities Identification Number (ISIN). A basic set of information is required to be reported on a security-by-security level. This includes the nominal amount and the market value of the securities, as well as the sectoral classification

[11] The dataset is also used in Fecht et al. (2018) and Abbassi et al. (2016).

and residency of the holder. Since January 2013, the reports are collected monthly, and since January 2014, the holdings are further disaggregated in securities in the trading portfolio, securities held to maturity, as well as securities lent or borrowed.

From this dataset, we extract the holdings for the 43 banks in our sample. These are the banks actively trading both bond and CDSs.Then, for each live security held, we extract additional characteristics at ISIN level from the CSDB database, describes in the previous paragraph. We extract instrument attributes (CFI codes, amount issued, amount outstanding, issue date, original maturity, residual maturity), issuer attributes (identifier, domicile, sector, NACE code), price data (monthly average price, volume traded), as well as coupon and redemption attributes.

Regarding the selection of the sample, we focus on bond holdings, as they are closest instruments to CDS when trading credit risk. For this, we select all securities with a CFI code starting with "D", and we drop warrants ("DW") and miscellaneous ("DM"). We also drop bonds with missing information on amounts issued, issue date, and maturity, as well as bonds with a residual maturity shorter than 90 days. The bond analysis follows the same period as the CDS analysis: 1 January 2014 to 30 June 2015, with three quarters as pre-treatment period and three quarters as post-treatment period. We collapse the data at bank - bond level, and we build balanced panels over the pre and post periods.

Our final dataset of bank bond holdings comprises 37,327 bonds issued by 4,544 firms. Table 4 shows descriptive statistics on the bond portfolios of the 43 German banks. 35% of the bonds held in the portfolios are issued by 387 firms with traded CDS. Among these, 17% (6.3% of total) of the holdings are hedged with CDS contracts, while 24% (9.4% of total) of the holdings are doubled up with sold CDS protection.

Table 4: . Summary Statistics: Bond Analysis

	N (1)	Mean (2)	SD (3)	P10 (4)	P50 (5)	P90 (6)
Bond Yield Analysis						
Bond Yields (in %)	13,627	2.76	2.08	0.62	2.18	5.75
Bank Bond Holdings						
CDS Buyer (in %)	52,338	6.27	24.24	0	0	100
CDS Seller (in %)	52,338	9.39	29.17	0	0	100
CDS Traded (in %)	52,338	35.11	47.73	0	0	100
Nominal Value (EUR 000,000)	52,338	6.97	46.21	0	0.13	11.11
Nominal Value (EUR 000,000)	52,338	7.15	46.69	0	0.14	11.57
Outstanding (EUR 000,000)	52,338	386.57	744.47	0.17	100	1,000
Amount Issued (EUR 000,000)	52,338	1,524.87	72,028.73	0.57	300	1,500
Original Maturity (Years)	52,338	7.90	8.66	2	6	12
Residual Maturity (Years)	52,338	1.66	5.01	0	0.11	3.55
Rating Score	52,338	11.82	9.07	1	9	23

This table reports summary statistics for the main variables employed in the bond and investor level analysis over the pre-period, that is, from January 2014 to September 2014.

3.2 Analysis of Bond Spreads

We start the bond-level analysis by investigating the effects of the CDS shock on corporate bond spreads. CDS markets are linked to bonds markets because they provide a means to insure exposures against default (hedging), because CDSs are alternative assets to trade credit risk (speculation or investing), or simply through the market pricing of credit risk as reflected in the CDS-Bond basis (arbitrage). In order to understand how strong these links are, we first study whether the negative CDS supply shock we explore has any impact on bond spreads. A negative impact is consistent with a strong hedging channel (as frictions affect trading the hedges, investors offload the underlying bonds which lowers prices and increases yields). A positive impact on bond spreads would be consistent with the speculation channel as investors look for substitute trading positions in the bond market. Finally, an increase in the CDS spreads that is matched by higher bond spreads is also consistent with no arbitrage conditions. We investigate these mechanisms by first studying the effects on bond yields, which we then follow up with an analysis of investor holdings.

For this, we extract from the CSDB database all bonds issued by corporations with traded CDS. We then estimate how bond yields vary with the treatment intensity, according to the following specification:

$$Log(yield_{bt}) = \beta TreatmentIntensity_b * Post_t + \alpha_t + \gamma_b + \mu_{bt} + \epsilon_{bt} \quad (4)$$

The dependent variable, $Log(yield_{bt})$ measures the logarithm of the yield to maturity on bond b in month t. α_t and γ_s are, respectively, month and bond fixed effects. μ_{bt} are time varying bond characteristics and they include the amount outstanding and the residual maturity of the bond. Finally, in some specifications we drop the month fixed effects and add macroeconomic controls which are measured on the same day as the bond yields. We control in this way for market volatility, CDS trading activity and risk free rates by including the VIX, the CDX and CDX high yield indices, as well as the USD and EUR swap rates with maturities of 1, 5 and 10 years. The specification therefore is in the spirit of a difference-in-differences analysis with heterogeneous treatment intensity. Effectively, the coefficient β measures the effect of the treatment intensity, within the group of bonds with traded CDSs, in the post-period.

Finally, in order to investigate how the effects vary with the underlying credit risk, we also interact the treatment variable in Equation (4) with the linear function of the rating score which we employed in the analysis of the CDS market.

3.3 Analysis of Investor Bond Holdings

In the last part of the analysis, we study whether investors adjust their bond portfolios in response to the shock in the CDS market. This unique perspective will allow us to draw conclusions regarding the mechanisms that could be driving any changes in bond spreads. For this, we augment the analysis with one crucial dataset - detailed bank bond holdings. By combining the bond holdings with the CDS position data, we can identify when investors hedge and double up their bond exposures by using the CDS. Subsequently, we study the elasticity of these bond holdings to the CDS market shock.

Using these investor-level bond portfolios, we estimate models explaining the rate of growth of holdings at investor $\times$ bond level. We treat the bonds on which the investor was long or short CDS protection, in the pre-period. To make sure that our results are not driven by selection on unobservables across issuers with traded CDS versus issuers without traded CDS, we first restrict the sample to the bond holdings corresponding only to issuers with traded CDS. In the appendix, however, we estimate the same specification on the full sample of holdings, and we include an additional indicator for all those bonds issued by firms with CDS traded globally. We estimate the following specifications:

$$\Delta Holdings_{ib,pre-post} = \alpha CDSBuyer_{ib} + \beta CDSSeller_{ib} + \gamma_i + \epsilon_{ib} \tag{5}$$

where $\Delta Holdings_{ib,pre-post}$ measures the change in bond holdings from the pre- to the post- period, for investor i and bond b. We calculate this rate of growth as follows:

$$\Delta Holdings_{ib,pre-post} = \frac{Holdings_{ib,post} - Holdings_{ib,pre}}{0.5 * (Holdings_{ib,post} + Holdings_{ib,pre})}$$

$CDSBuyer_{ib}$ is a dummy variable that equals 1 if the investor had CDS protection on bond i in the pre-period, and zero otherwise. $CDSSeller_{ib}$ is a dummy variable that equals 1 if the investor had doubled up on their bond holdings i by selling CDS protection in the pre-period, and zero otherwise. γ_i are investor fixed effects. We therefore investigate different trends in portfolio rebalancing, depending on whether the banks were active buy or sell CDS investors on the same bonds they held. By means of this specification, we simultaneously compare how a single bank adjusts its portfolio of a hedged bond versus a non-hedged bond position (within investor), and how a bank with a hedged bond position rebalances holdings with respect to a different bank holding the same bond, but not the CDS (across investors).

While the base specification is equivalent to including bond fixed effects, we saturate the model further with investor, investor $\times$ industry, investor $\times$ country, and investor $\times$ rating score. We cluster standard errors at issuer level. Finally, we explore how the effects vary with the riskiness of the underlying by separating the analysis in rating buckets as well as by interacting the dummy variables $CDSBuyer_{ib}$ and $CDSSeller_{ib}$ with the linear function of the rating score.

3.4 Results

The estimates in Table 5 reveal that the supply shock in the CDS market raises bond yields. On average over the sample, a 10pp increase in treatment intensity leads to a 2% increase in the average yield, or the equivalent of 6bps. Interacting the treatment intensity measure with the rating score shows that the effect is increasing with the riskiness of the bond: the link with the derivative market is strongest for the riskiest bonds.

The results thus suggest that changes in the liquidity of CDS markets affect the secondary bond markets. Moreover, the two assets appear to be complementary. The increase in the cost of the hedge is followed by an increase in the cost of the underlying. Finally, the effects could also transmit to the primary markets: in fact, both the price as well as the ease of selling a bond in the secondary market are likely to be very important determinants of primary market yields.

Table 5: . Effect on the Yields of CDS Traded Bonds

	Log(Bond Yield)			
	All			Sensitivity to Rating
	(1)	(2)	(3)	(4)
$TreatmentIntensity \times Post$	0.021***	0.021***	0.022***	0.001
	(0.005)	(0.005)	(0.005)	(0.009)
$Post$	-0.002	-0.001		
	(0.036)	(0.036)		
$TreatmentIntensity \times Post \times RatingScore$				0.004***
				(0.000)
$RatingScore \times Post$				0.010***
				(0.002)
Macro Controls	Yes	No	No	No
Bond Controls	Yes	Yes	Yes	Yes
Bond Fixed Effects	Yes	Yes	Yes	Yes
Month Fixed Effects	No	Yes	Yes	Yes
Observations	25,160	25,160	25,160	25,160
R^2	0.933	0.943	0.927	0.905

This table estimates the effects of the CDS dealer exit on the yields of bonds issued by the top 1,000 CDS traded reference entities. The unit of observation is bond × month. The yield of the bond is collected at month end. $TreatmentIntensity$ is the CDS market share of the dealer for each of the 1,000 top CDS reference entities. $Post$ takes value 0 between January to September 2014 and 1 between October 2014 to June 2015. $RatingScore$ is a linear function of the rating of the bond. Macro controls include the VIX, CDS trading indexes CDX and CDX HY, as well as dollar and the euro swap rates for 1 year, 5 years and 10 years maturities. Time varying bond controls include the logarithm of the outstanding amount and of the residual maturity. The coefficients on the treatment intensity are directly evaluated at a 10pp standard deviation. Standard errors are clustered at industry and month, and are reported in brackets, $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Finally, we study bank bond portfolios in order to understand the drivers behind the increase in bond yields. In particular, while Siriwardane (2019) presents evidence supporting the no arbitrage channel, we find that the hedging channel is also a driver of bond spreads. Table 6 shows that the investors using the CDS as a hedging device for their existing bond exposures reduce their affected bond holdings after the shock. The results hold and are relatively stable as we saturate the models with investor and industry, country or rating fixed effects. Moreover, Table 10 in the appendix shows similar results coming from the estimations on the full sample of bond holdings.

Table 6: . Bond Divestments - Hedging Portfolios vs. Investment Portfolios

	Pre/Post Change in Bond Holdings at Investor × Bond Level				
	Delta Holdings				
	(1)	(2)	(3)	(4)	(5)
CDS Buyer	-0.188***	-0.199***	-0.157***	-0.132**	-0.115**
	(0.053)	(0.052)	(0.055)	(0.055)	(0.051)
CDS Seller	-0.046	-0.085*	-0.087	-0.096*	-0.027
	(0.057)	(0.049)	(0.058)	(0.055)	(0.047)
Bond FE	Yes	Yes	Yes	Yes	Yes
Investor FE	No	Yes	No	No	No
Investor × Industry FE	No	No	Yes	No	No
Investor × Country FE	No	No	No	Yes	No
Investor × Rating FE	No	No	No	No	Yes
Observations	21,310	21,310	21,310	21,310	21,310
R^2	0.006	0.018	0.035	0.060	0.049

This table reports the coefficients of linear regressions where the dependent variable is the change in bank bond holdings between the pre and post period. The independent variable, *CDS Buyer*, is an indicator variable that takes value one if the investor hedged the position in the pre- period (i.e., if the investor has purchased both the bond and CDS protection on the issuer). *CDS Seller* takes value one if the investor used the CDS market to double up on credit risk exposure (i.e., if the investor has purchased the bond and it has sold CDS protection on its issuer). In this table the sample of bonds includes only bonds issued by corporations with traded CDS, while Table 10 in the Appendix estimates the same specifications, but on the full sample of bonds. The unit of observation is bank *times* bond, and the specifications include, in turn, investor fixed effects, investor × industry fixed effects, investor × issuer country, and investor × rating bucket fixed effects. Standard errors are clustered at issuer firm level and reported in brackets, $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Finally, we study how the effects vary with the risk of the underlying issuer. In Table 7, we study how the estimates vary with the rating class. The effects are more pronounced for the relatively riskier bonds: lower-investment grade, speculative and below speculative bond holdings are the most reactive. These results hold in the full sample, as illustrated in Table 11.

Table 7: . Overall Effects on Bond Exposures by Rating Class

	Pre/Post Change in Bond Holdings at Investor × Bond Level					
	All	Prime & High	Upper Medium	Lower Medium	Speculative & Below	Interaction w. Score
	(1)	(2)	(3)	(4)	(5)	(6)
CDS Buyer	-0.188***	0.004	-0.126	-0.138**	-0.332***	0.077
	(0.053)	(0.088)	(0.094)	(0.066)	(0.115)	(0.078)
CDS Seller	-0.046	-0.020	-0.018	0.119**	-0.184	0.099
	(0.057)	(0.072)	(0.090)	(0.054)	(0.128)	(0.073)
Rating Score						0.013***
						(0.006)
CDS Buyer × *Rating Score*						-0.023***
						(0.008)
CDS Seller × *Rating Score*						-0.013
						(0.008)
Bond Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21,310	2,975	4,076	3,364	10,895	21,310
R^2	0.006	0.000	0.001	0.004	0.005	0.008

This table reports the coefficients of linear regressions where the dependent variable is the change in bank bond holdings between the pre and post period. The independent variable, *CDS Buyer*, is an indicator variable that takes value one if the bank has purchased both the bond and CDS protection on it. *CDS Seller* takes value one if the bank has purchased the bond and it has sold CDS protection on it. The unit of observation is bank *times* bond, and since we model rates of growth, the models are equivalent to including bond fixed effects. *RatingScore* is a linear function of the long term rating assigned by one of the three main rating agencies. The score ranges from 1, in the case of a triple AAA or prime bond, to 23 for non-rated bonds. In this table the sample of bonds includes only bonds issued by corporations with traded CDS, while Table 11 in the Appendix estimates similar specifications, but on the full sample of bonds. We estimate the models in turn for different rating buckets, and by interacting the investor dummies with the score measure. Standard errors are clustered at issuer firm level and reported in brackets, $^{\star}p < 0.10$, $^{\star\star}p < 0.05$, $^{\star\star\star}p < 0.01$

4 Conclusion

We study the direct and spillover effects on CDS and bond markets of an event that negatively affects CDS market liquidity. We document causal evidence that CDS traded volumes decrease and bid-ask spreads increase for affected reference firms. This negative shock to the liquidity of the CDS market affects the secondary market for bonds, most likely through the hedging channel. We find that bond yields of CDS traded firms increase proportionally to the ex-ante market share of the exiting dealer. Moreover, investors engage in portfolio rebalancing and sell the bonds on which they had previously purchased credit protection. The effects are concentrated in the lower rating buckets.

Possible ways of correcting these negative externalities require intervention to increase the competitiveness of and ease of entry into OTC markets, or the direct provision of liquidity in times of stress.

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C.APPENDIX

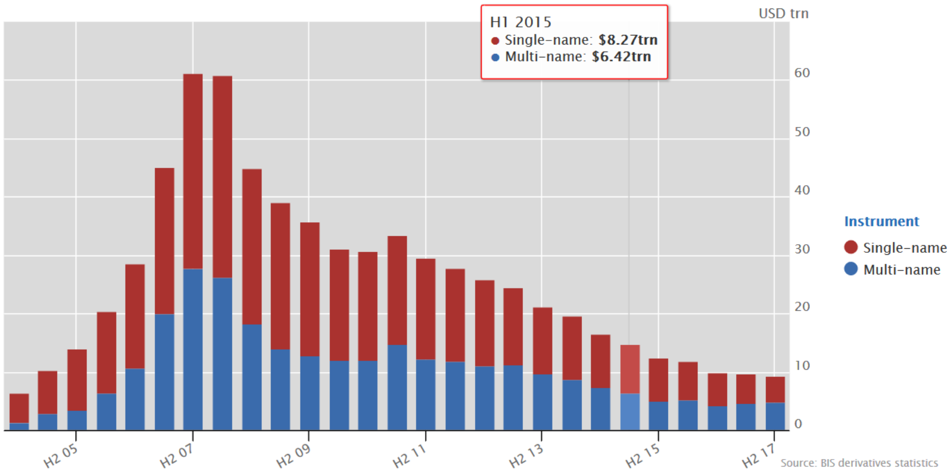

Figure 6: . The Evolution of the CDS Market since 2005

This figure shows the evolution of the outstanding notionals in the CDS market for single-name and multi-name reference entities since 2005. The data underlying the figure comes from BIS Statistics.

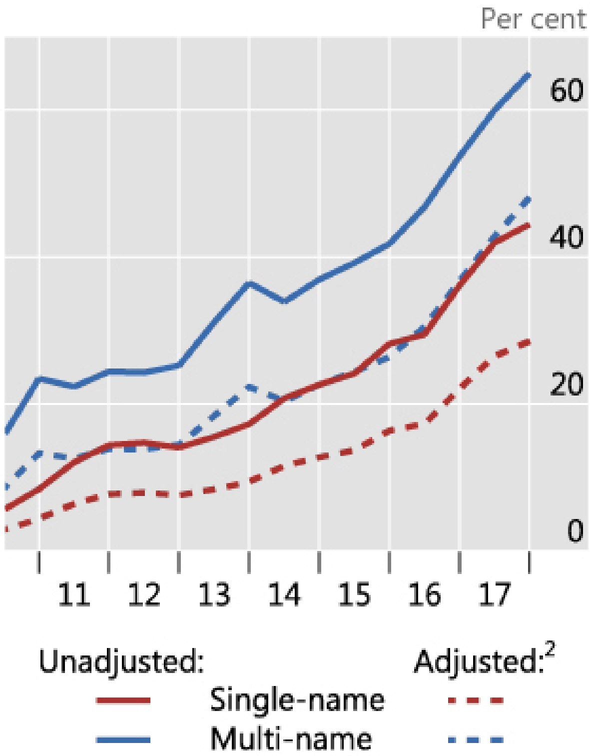

Figure 7: . Penetration of Clearing in the CDS Market

This figure shows the evolution of clearing in the CDS market for single-name and multi-name reference entities. The data underlying the figure comes from BIS Statistics.

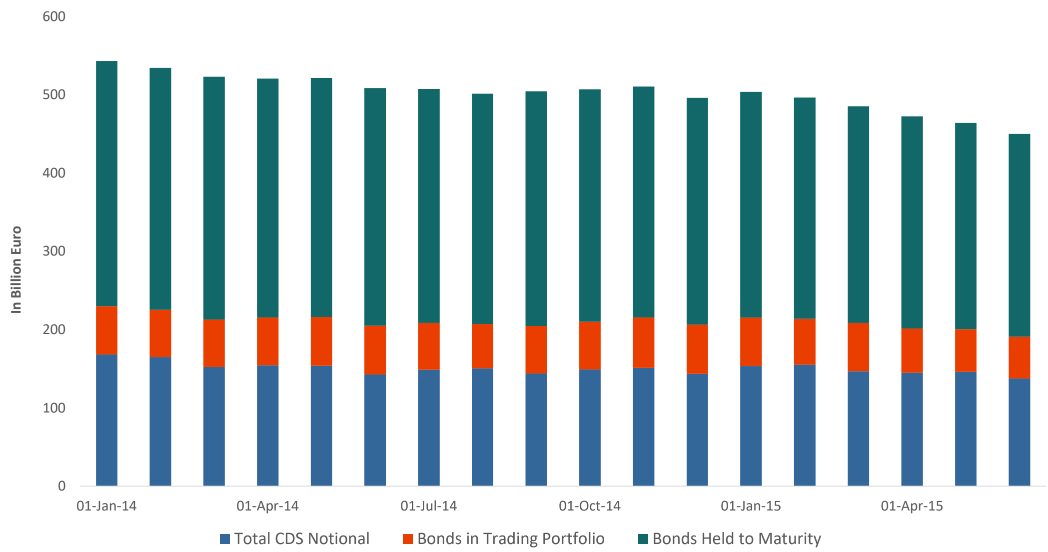

Figure 8: . Single Name CDS and Bond Holdings of German Banks In Sample

This figure illustrates the aggregated holdings of CDS and bonds for the 43 banks in the analysis sample. The underlying data comes from DTCC & the Security Holdings Statistics of the Deutsche Bundesbank.

Table 8: . Effect on the Probability to Trade CDS

	Probability of Trading - Linear Probability Model					
Sample	All				Buy Trades	Sell Trades
	(1)	(2)	(3)	(4)	(5)	(6)
$TreatmentIntensity \times Post$	-0.148***	-0.148***	-0.131***	-0.130***	-0.151***	-0.109**
	(0.046)	(0.046)	(0.046)	(0.047)	(0.0487)	(0.0484)
$Post$	-0.114***	-0.114***	-	-	-	-
	(0.010)	(0.010)	-	-	-	-
$TreatmentIntensity$	0.131***	0.129***	0.124**	0.179**	0.145*	0.215***
	(0.043)	(0.0476)	(0.048)	(0.072)	(0.074)	(0.074)
Investor FE	No	Yes	No	No	No	No
Investor X Quarter FE	No	No	Yes	Yes	Yes	Yes
Reference Firm Controls	No	No	No	Yes	Yes	Yes
Observations	194,572	194,572	194,572	194,572	96,040	96,936
R^2	0.024	0.053	0.090	0.032	0.147	0.131

The table reports the coefficients of linear probability models where the dependent variable measures the likelihood that an investors enters a new CDS contract on a reference entity, in a given quarter. The unit of observation is at investor $\times$ reference entity $\times$ quarter, and the panel is balanced. The analysis runs from January 2012 until June 2015. $Post$ takes value 1 from in the post-period (October 2014 to June 2015), and value 0 otherwise. $TreatmentIntensity$ is the market share of the dealer calculated for each of the 1,000 top CDS reference entities. The coefficients on the treatment intensity are directly evaluated at a 10pp standard deviation. In the first table, we start with Model (1), which is a simple difference-in-differences specification. In Model (2), we add investor fixed effects. Model (3) adds investor $\times$ quarter fixed effects, and in Model (4) we add controls for the reference entity (country, industry and rating). Models (5) and (6) are estimated on the groups of buy and, respectively, sell trades. In the online appendix, Models (7) to (9) show the robustness of Model (1) to including time trends for investor, investor $\times$ industry, investor $\times$ country, and investor $\times$ rating bucket. Standard errors are clustered at reference entity and reported in brackets, $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 9: . Effect on the Probability to Trade CDS - Robustness to Trends

	Probability of Trading - Robustness to Time Trends				
	(1)	(7)	(8)	(9)	(10)
$TreatmentIntensity \times Post$	-0.148**	-0.126**	-0.140**	-0.194***	-0.141**
	(0.0459)	(0.0452)	(0.0453)	(0.0584)	(0.0460)
$Post$	-0.114***	-0.0262*	-0.0234*	-0.0128	-0.0232*
	(0.0100)	(0.0109)	(0.0110)	(0.0131)	(0.0110)
$TreatmentIntensity$	0.131**	0.129**	0.124*	0.179*	0.145
	(0.0425)	(0.0476)	(0.0487)	(0.0721)	(0.0747)
Investor Trends	No	Yes	No	No	No
Investor X Industry Trends	No	No	Yes	No	No
Investor X Country Trends	No	No	No	Yes	No
Investor X Rating Trends	No	No	No	No	Yes
Observations	194,572	194,572	194,572	194,572	194,572
R^2	0.024	0.070	0.089	0.124	0.083

The tables reports the coefficients of linear probability models where the dependent variable measures the likelihood that an investors enters a new CDS contract on a reference entity, in a given quarter. The unit of observation is at investor $\times$ reference entity $\times$ quarter, and the panel is balanced. The analysis runs from January 2012 until June 2015. *Post* takes value 1 from in the post-period (October 2014 to June 2015), and value 0 otherwise. $TreatmentIntensity$ is the market share of the dealer calculated for each of the 1000 top CDS reference entities. Finally, in the second table, Models (7) to (9) show the robustness of Model (1) to including time trends for investor, investor $\times$ industry, investor $\times$ country, and investor $\times$ rating bucket. Standard errors are clustered at reference entity and reported in brackets, $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 10: . Bond Divestments - All Bonds

	Change in Bond Holdings at Investor X Bond				
	Delta Notional				
	(1)	(2)	(3)	(4)	(5)
$CDS \quad Buyer$	-0.289***	-0.241***	-0.239***	-0.165***	-0.205***
	(0.061)	(0.049)	(0.054)	(0.044)	(0.046)
$CDS \quad Seller$	-0.147**	-0.103*	-0.141**	-0.103*	-0.052
	(0.066)	(0.059)	(0.065)	(0.054)	(0.0488)
$CDS \quad Traded$	0.164***	0.174***	0.149***	0.135***	0.102***
	(0.062)	(0.057)	(0.054)	(0.039)	(0.038)
Bond FE	Yes	Yes	Yes	Yes	Yes
Investor FE	No	Yes	No	No	No
Investor × Industry FE	No	No	Yes	No	No
Investor × Country FE	No	No	No	Yes	No
Investor × Rating FE	No	No	No	No	Yes
Observations	59,287	59,287	59,287	59,287	59,287
R^2	0.023	0.047	0.056	0.061	0.050

This table reports the coefficients of linear regressions where the dependent variable is the change in bank bond holdings between the pre and post period. The independent variable, *CDS Buyer*, is an indicator variable that takes value one if the bank has purchased both the bond and CDS protection on it. *CDS Seller* takes value one if the bank has purchased the bond and it has sold CDS protection on it. Finally, *CDS Traded* takes value one for bonds issued by corporates on which there are CDS traded. The unit of observation is bank *times* bond, and the specifications include, in turn, bank fixed effects, bank × industry fixed effects, bank × issuer country, and bank × rating bucket fixed effects. Standard errors are clustered at issuer firm level and reported in brackets, $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 11: . Overall Effects on Bond Exposures by Rating Class

	Change in Bond Holdings at Investor X Bond				
	Prime	High	Upper Medium	Lower Medium	Speculative & Below
	(1)	(2)	(3)	(4)	(5)
CDSBuyer	0.143	-0.084	-0.189***	-0.164**	-0.492***
	(0.141)	(0.096)	(0.066)	(0.071)	(0.155)
CDSSeller	-0.164	0.051	-0.012	0.046	-0.256**
	(0.111)	(0.095)	(0.069)	(0.057)	(0.117)
CDSTraded	0.031	0.166***	0.102	0.009	0.163*
	(0.087)	(0.064)	(0.072)	(0.072)	(0.087)
Bond Fixed Effects	Yes	Yes	Yes	Yes	Yes
Investor Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	9,068	4,825	8,935	6,653	26,884
R^2	0.025	0.024	0.027	0.030	0.046

This table reports the coefficients of linear regressions where the dependent variable is the change in bank bond holdings between the pre and post period. The independent variable, *CDS Buyer*, is an indicator variable that takes value one if the bank has purchased both the bond and CDS protection on it. *CDS Seller* takes value one if the bank has purchased the bond and it has sold CDS protection on it. Finally, *CDS Traded* takes value one for bonds issued by corporates on which there are CDS traded. The unit of observation is bank *times* bond, and the specification include, in turn, bank fixed effects, bank × industry fixed effects, bank × issuer country, and bank × rating bucket fixed effects. We estimate the models in turn for the different rating classes. Standard errors are clustered at issuer firm level and reported in brackets, $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

The Value of Bank Privileged Information: Evidence from the CDS Market *

Andrada Bilan[†] Steven Ongena[‡] Cosimo Pancaro [§]

Abstract

Are banks able to trade corporate credit default swaps (CDSs) at competitive prices, or are they penalized for potentially holding privileged information on their borrowers? We use the EMIR CDS transaction dataset to address this question. By comparing the prices that the same dealer offers to banks and to other investors for similar contracts, we find that banks are able to trade at a discount. Dealers find bank trades valuable and are willing to compensate banks for their business. Subsequently to trading with a bank, dealers stand to gain from trading with other investors, on the same entity. Our findings suggest that banks hold private information which they are willing to share with dealers in exchange for competitive access to derivatives.

Keywords: Dealer Markets, Banks, Price Discovery, CDS, EMIR

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1 Introduction

For a simple way to unload risk from their corporate portfolios, banks can trade credit derivatives, such as credit-default swaps (CDS). In fact, the Basel III rulebook allows banks to obtain regulatory capital relief when selling the credit risk associated with lending exposures. In a typical transaction, the bank purchases CDS protection from an OTC market dealer, who assumes the position. The dealer then searches for a counterparty, a CDS protection seller, typically among hedge funds, pension plans, insurances, or other banks' trading desks.[1] In exchange for paying a regular fee - the CDS spread or coupon - the bank receives a lump sum payment if borrower quality deteriorates enough to cause bankruptcy or suspension of payments. Crucially, ex-ante, when calculating capital requirements, this transaction allows the bank to reduce the risk weight associated with the hedged loan exposure.[2] Therefore, as long as the premia banks pay for protection is sufficiently competitive - that is, lower than the opportunity cost of capital requirements - banks will rely on derivatives in their risk management practices. In this case, the CDS market can enhance the function of macro-prudential policies in disciplining banks ex-ante, thus avoiding the build-up of risks and reducing the need to trigger capital buffers.

But do CDS markets function properly and can banks use them to purchase credit insurance on equal terms as other investors? This is not a trivial question. Because banks are likely informed investors, it is conceivable that they have to pay a 'lemons premium' when buying default protection on their own customers. However, it can also be conceived that banks might enjoy a discount when trading in the CDS markets. If trades with banks disclose private information, derivative dealers could then monetize this information when trading with other investors. This research question can only be answered by studying transaction-level micro-

[1]While banks can theoretically also purchase more complex products such as first-loss CDS protection on pools of loans, the markets for these products are typically far less liquid.

[2]In effect, after purchasing CDS protection, risk weights on loans which vary between 100 and 1250 are replaced with a lower 100 percent risk weight assigned to the counterparty credit risk of the dealer that sold the credit protection.

data. Such data permits comparisons of the trading terms that dealers offer to banks and to other investors, for otherwise equal contracts.

In this paper we use data on credit default swap transactions made available through the European Market Infrastructure Regulation (EMIR) to shed new light on the trading patterns of banks in this OTC market. Our focus is on the universe of credit default swap transactions concluded on single-name reference entities. The dataset contains detailed information on the identity of the counterparties to a transaction, the identity of the issuer, the exact time of the trade, the direction of the trade (a sell or a buy), notional values and currencies, prices, transaction fees, volumes, maturities and settlement dates, as well as the legal definitions that govern the settlement of the contracts in case of default. To all this, we add information provided by CMA through Bloomberg on CDS dealer quotes for the most liquid contract, as well as issuer ratings from the three rating agencies (Fitch, Moody's and S&P).

The identification strategy relies on three elements: (1) the availability of pricing information, at trade level; (2) the identity of the trading parties; and (3) detailed fixed effects and contract characteristics to account for the heterogeneity of the trades. Using the EMIR dataset on CDS transactions, we measure whether there is any bias in the trading prices that dealers offer to banks relative to other investors, controlling for differences in the contracts traded. Because we have detailed trade-level data, our estimations can control, both parametrically and non-parametrically, for the main contract characteristics (maturity, coupon, seniority and notional traded). In the most restrictive specifications, we add dealer $\times$ reference firm $\times$ month fixed effects, effectively measuring whether the same dealer offers a different price to banks versus other investors for a contract on the same reference firm, signed during the same month.

Next, we study whether there is any price impact following trades that dealers conclude with banks. We construct measures of the price impact of trading with a bank at two horizons: one week and one month, as follows. We construct a dummy variable that takes the value one the week or month following a dealer's trade with a bank, whenever the dealer trades with non bank investors on the same reference entity. The dummy takes value zero for the remaining trades.

Finally, we investigate whether any bank bias affects the actual cost of credit risk, or just the transaction costs of the trades. For this, we study the effects on the realized bid-ask spreads. We match the contracts in our sample with publicly available information on CDS mid quotes, in order to arrive at estimates of the spreads. For every contract, we then calculate the absolute deviation between the price of the contract (bid or ask), and the quoted mid. This gives us the half spreads, which we use as dependent variables in models where the main explanatory variable is the identity of the investor. We also investigate how the effects vary with the ex-ante credit quality of the underlying obligation, by separately estimating the models by rating class.

The results of the pricing analysis suggest that banks indeed are offered different prices relative to other investors, when trading credit risk through CDS contracts. The bias is negative - that is, bank trades carry a discount -, suggesting that bank trades are valuable for dealers, plausibly because of their informational content. Our most restrictive estimates suggest that the same dealer selling the same CDS protection contract during the same month to a bank and to another investor, will charge the bank an upfront payment lower by 1pp. In monetary terms, this amounts to a net present value of EUR 50,000, calculated over the life of a five-year CDS contract with a standard notional of five million. The effects are smaller in magnitude, but still significant, for sell trades.

Moreover, we find evidence that trades with banks have a price impact over both one week and one month horizons. After trading with banks at a discount, dealers are able to extract larger payments from other investors, when trading on the same reference firm. Again, this is suggestive of the fact that dealers are learning valuable new information after trading with banks. Next, we document that the discount enjoyed by banks is not only due to the reduction in transaction costs, but that actual cost of CDS protection they pay is lower. For a standard CDS protection contract, 25% of the bank discount is transmitted through transaction costs - in the form of narrower bid-ask spreads -, while the remaining 75% of the discount comes from a lower cost of protection. Finally, when investigating the heterogeneity of the effect across ex-ante credit risk, we find stronger estimates for reference entities with speculative or no rating.

Overall, our findings suggest that banks can purchase CDS protection on more affordable terms than other investors. As a result, the derivative can be particularly useful in bank risk management practices, and it can help transmit valuable information from banks to the rest of the financial market. These findings are of particular relevance given the recent developments in macroprudential policy, aiming to deal with cases where there is risk build-up in the financial sector. For example, in Europe, new EU prudential rules for banks entered into force at the start of 2014, allowing member states to increase capital requirements through countercyclical or systemic buffers to address eventual vulnerabilities. Such macroprudential tools aim at disciplining banks ex-ante because they provide the right incentives for banks to engage in safe lending and sound risk management practices.[3] But such efficient and timely risk management requires that banks be able to trade risks in competitive and liquid derivative markets. CDS contracts offer this possibility.

2 Relevance to Literature

First, it is necessary to investigate empirically whether the presence of imperfect information distorts the functioning of financial markets. Banks are useful in this sense, because they hold private information on their borrowers (Fama 1985; James

[3]When capital requirements are raised ex-post without giving banks sufficient time to correct their risk-taking, banks can reduce lending, which has negative real effects (Behn et al. 2016; Jiménez et al. 2017).

1987). When the payoff of the uninformed party to the financial contract does not depend on the private information, the competitive equilibrium is efficient (Fagart 1996). On the contrary, markets can break down in the presence of so-called 'common values' when the hidden information of the informed party affects the payoff of the uniformed party (Akerlof 1978; Rothschild and Stiglitz 1978). This could occur in the CDS market. When a bank approaches a CDS dealer looking to purchase credit protection on a borrower, the dealer cannot know for sure whether the bank is seeking capital relief or if the bank has received a negative private signal on the quality of its borrower. Such asymmetries can raise the premium that banks pay on CDS protection, possibly to prohibitive levels. This is in line with basic insights from market microstructure suggesting that liquidity dries up and spreads widen in the presence of informed traders (Kyle 1985; Glosten and Milgrom 1985).

Second, it is important to understand how informed trading affects price discovery. In fact, it could well be that market makers transact CDS with banks at a discount, in order to purchase their privileged information. Then, the information surplus would be shared between the bank and the market maker, who expects to monetise it by trading with uninformed investors. This interpretation is consistent with recent empirical evidence suggesting that creditors earn abnormal returns when trading in related equities. Ivashina and Sun (2011) combine quarterly stock holdings and information on lending relationships. They find that institutional investors who are privy to loan amendments obtain excess returns when trading in the stock of the borrowers. Addoum and Murfin (2017) measure for how long information generated within lending relationships is valuable in the equity market. They show that trading equities based on publicly disseminated loan prices can lead to abnormal returns up to two months following their release. Acharya and Johnson (2007) look at the CDS market and document how CDS spreads lead equity prices, especially ahead of bad news and for firms with multiple banks. These findings, they argue, are consistent with the presence of informed trading by banks in the CDS market. Contrary to the argument developed in the previous paragraph, in this scenario, banks would actually have access to relatively cheaper credit protection from their dealers.

The empirical evidence on whether banks actually trade CDS for hedging purposes is mixed. Saretto and Tookes (2013) show that lenders appear more willing to extend credit to firms with traded CDS and that this intensifies in the presence of capital constraints, something which is consistent with the use of CDS markets to hedge and manage capital. Gunduz et al. (2017) find that banks rely increasingly on CDS as hedging tools after CDS contracts became more standardized and hence cheaper to trade for all investors. However, Aldasoro and Barth (2017) match CDS positions with syndicated loans on European corporates and find little evidence that banks use CDS for capital relief. Moreover, none of these studies compares the trading terms that dealers offer to bank versus non-bank investors, in order to study whether holding private information enables or hurts CDS trading by banks.

Third, the linkages between credit derivatives and corporate lending markets have still not been fully explored. Most of the recent literature on this topic points to the negative effects of CDS trading on lending to corporates. Ashcraft and Santos (2009) compare firms with and without CDS trading and find that the onset of CDS trading does not lower bond or loan spreads for the average firm. They document a small positive effect on safe and transparent firms as well as an adverse effect on opaque and risky firms. The latter could be rationalised if CDS trading reduces lenders' incentives to monitor. Amiram et al. (2017) explore this effect further. They show that CDS trading on a firm's debt increases the share of loans retained by loan syndicate lead arrangers, in an effort to reinforce their commitment to monitoring.

Another adverse effect of CDS trading is related to the occurrence of 'empty creditors' or lenders that retain control rights but not the economic exposures to the underlying firms. Consistent with the existence of empty creditors, Subrahmanyam et al. (2014) find that, after the inception of CDS trading, the probabilities of credit rating downgrades or of bankruptcy increase substantially. Nonetheless, Oehmke and Zawadowski (2016) uphold the importance of CDS markets using investor-firm level data on CDS positions and bond issuances. Investors - they argue - still use the CDS market for both hedging - with CDS volumes increasing in bonds outstanding -, and speculation - with CDS volumes increasing with analyst disagreement. But is there a silver lining in the interaction between the CDS market and the banking market? It remains to be established whether trading CDS allows banks to disseminate risks and information, potentially reinforcing macro stability and price informativeness.

3 Data Description and Summary Statistics

This section reviews the data employed in the analysis, the cleaning procedures, and it presents some summary statistics. We use three different databases: the set of Euro-area CDS transactions available through EMIR at the European Central bank, daily CDS benchmark prices sourced from Bloomberg covering the most liquid contract types, and ratings information from Fitch, Moodys, and S&P.

3.1 EMIR CDS Transactions Database

The EMIR database available at the ECB contains information on derivative transactions in which at least one counterparty to the trade, or the reference entity on which the trade is written, is headquartered in a Euro-area country.

Reporting to the EMIR dataset has been ongoing on a daily basis since 2014, covering five asset classes: equity, credit, interest rate, commodity, and foreign exchange. The reports include both transactions (the flow of new trades) and positions (the stock), and the reporting obligation is two-sided, which means that both counterparties to the trade have to submit the report. This is big data: approximately one hundred million observations per day, each containing nearly two hundred and fifty attributes, amounting to about one terabyte of daily information.

Our project focuses on the universe of credit default swap transactions concluded on single-name reference entities. The dataset contains detailed information on the identity of the counterparties to a transaction, the exact time of the trade, the direction of the trade (a sell or a buy), notional values and currencies, prices, transaction fees, volumes, maturities and settlement dates, as well as the legal definitions that govern the settlement of the contracts in case of default.

We were granted access to the CDS transaction data over the period January 2018 to June 2019. The initial CDS transaction dataset covering this time horizon has 2.8 million entries. We keep only single-name trades, that is, those trades written on a single obligation, with an underlying ISIN. This results in 1.1 million entries. We further keep only contracts identified as "swap", accounting for 82% of the sample. In doing so, we drop other contract types such as credit futures, forwards, options, or less standardized trades. We also drop entries marked as compression trades, and restrict the sample to trades with a price expressed in percentage of notional. Finally, we keep trades where the notional is expressed in either euros or US dollars. After applying these filters, our sample comprises a little above one million trades.

Because our study is focused on pricing patterns, an important filter we apply on the raw trades is to select the contracts priced according to standard conventions. These are contracts that follow the definitions set in the Big Bang and Small Bang protocols, and are fairly homogeneous and priced upfront. In particular, under the fixed legal definitions, the contracts have pre-set maturity dates (the four yearly IMM dates), fixed notional amounts (5 or 10 million), and fixed protection coupons of typically 100bps or 500bps. Because the coupons are fixed, the price of this contract is exchanged upfront, and it amounts to the discounted value of the difference between the market value of the coupon and the fixed rate. When the seller of CDS protection estimates the value of the protection coupon to be higher than the market value, the protection buyer makes an upfront payment to the protection seller. Conversely, when the dealer estimates that the fixed coupon is too high a price for protection, the CDS protection buyer receives an upfront payment from the seller. After keeping only standard contracts with fixed maturities and fixed coupons of 100 or 500 basis points, we are left with 310,000 transactions in the sample.

Finally, we add some additional information on the identities of the parties and reference entities. For this, we first add unique names for the issues, based on Bloomberg information on the ISIN of the reference entity. We find matching reference entity names for 294,000 transactions. CDS transactions typically occur between a dealer and a buyside investor. We identify dealers based on the names of the counterparties to the trades.[4] We only keep trades for which at least one counterparty to the trade is a dealer, restricting the trades to two types: dealer-to-dealer (D2D), and dealer-to-customer (D2C). The sample of CDS transactions we therefore use in the first part of the analysis includes 291,591 individual entries.

Figures 1-3 and Table 1 offer a descriptive view of this sample, as well as summary statistics. The dataset is composed by 14 dealers sitting on one side of the trade, and transacting with 2,300 counterparties on 866 reference firms. Out of the 291,591 trades, 99,236 are dealer-to-dealer (34% of the sample), while 192,355 are dealer-to-buyside (66% of sample). 75 of the buyside investors are banks, and they are counterparties to 44,933 trades (15% of total). Importantly, the dataset is sufficiently rich to allow us to saturate our empirical specifications with fixed effects at the level of dealer *times* issuer *times* month, and to capture differences in trading terms by counterparty type (bank versus non bank). There are 44,392 non-empty groups at the level of dealer-issuer-month-investor type, 40% of which contain trades realized by both bank and non-bank buyside investors.

Most of the analysis focuses on the D2C market. Assuming D2C trades are client initiated allows us to sign these trades. Knowing the direction of the trade is indispensable for the price analysis of the upfront fees. For the analysis of the bid-ask spreads we use also the full sample of trades, since we focus on the absolute difference between the upfront payment and the quoted upfront mid.

3.2 CDS quotes

Part of our analysis studies the bid-ask spreads realised on the transactions. Because the CDS market is not very liquid to estimate mid prices directly from daily

[4]We identify the dealers in the sample based on the list of primary dealers provided by the New York Fed, and available at: https://www.newyorkfed.org/markets/primarydealers.

prices, we calculate half spreads as the absolute difference between the bid or the ask upfront prices and a benchmark mid upfront price. We use daily quoted mid upfronts sourced from CMA through Bloomberg. We match the quotes with our dataset of CDS trades based on reference firm, date, currency, seniority, and tenor. Our final dataset contains 184,964 trades. 15% of the trades have a bank as a buy-side counterparty. In total, there are 14 dealers, trading on 746 reference firms with 2,188 buyside investors out of which 72 are banks.

We therefore define the absolute half spread on a CDS contract traded on reference entity f entered at time t as follows:

$$
\begin{aligned}
|HalfSpread_{ft,s}| =& (UpfrontAsk_{ft} - UpfrontMid_{ft}) * \mathbf{1}[s \in selltrade] \\
& - (UpfrontBid_{ft} - UpfrontMid_{ft}) * \mathbf{1}[s \in buytrade]
\end{aligned}
$$

The $UpfrontAsk_{it}$ and the $UpfrontBid_{it}$ are the realised transaction prices. The $UpfrontMid_{it}$ is the daily Bloomberg indicative dealer mid quote, which we calculate as the average of the quoted bid and ask, and s is the direction of the trade. The average half spread is 0.06%.

3.3 Ratings

A third dataset used in the analysis contains ratings information from the S&P, Moodys and Fitch. We build a linear rating score, allocating a number to each rating class. This score function ranges between 1 (prime rated) to 23 (no rating), and we employ it throughout the analysis in order to control for publicly available information on the credit risk of the reference entity.

4 Empirical Strategy

The empirical strategy follows four steps. In the first step, we study whether CDS dealers offer different pricing terms to bank and non bank buyside investors, controlling for contract characteristics and for detailed fixed effects. For this, we use the realized upfront transaction prices that are recorded for every trade. In a second step, we investigate whether there is any meaningful price impact of trades with banks, by looking at any pricing bias that might arise when dealers trade with other investors, *subsequently to trading with a bank, but on the same reference entity.* Third and fourth steps follow the same type of analysis, but we study the impact on realized bid-ask spreads, instead of on the transaction upfront prices.

4.1 Analysis of Upfront Prices Paid by Banks

Using the EMIR dataset on CDS transactions, we measure whether there is any bias in the trading terms CDS market makers offer to bank relative to non-bank investors, for equal contracts. For this, we estimate the following specification:

$$\begin{aligned} Upfront_{idft} =& \beta * \mathbf{1}[buyside_i \in bank] + \alpha_d + \theta X_c + \sum_k \gamma_k * \mathbf{1}[maturity_i \in k] + \\ &+ \sum_p \gamma_p * \mathbf{1}[coupon_i \in p] + \sum_r \gamma_r * \mathbf{1}[seniority_i \in r] + \epsilon_{idft} \end{aligned}$$

In this model, the dependent variable, $Upfront_{idft}$, captures the upfront price realized on contract i, sold by dealer d, on reference entity f, at time t. The term $\mathbf{1}[buyside_i \in bank]$ takes value one when the CDS contracts are sold to banks and the estimate β picks up any pricing bias incurred by banks. In a series of estimations, the model includes fixed effects at the lever of the *dealer*, *industry* and *month*, as well as *dealer X reference entity* and *dealer X reference entity X time.* In the latter case, β measures whether the same dealer offers banks and non-bank investors different terms on contracts written on the same reference entities, for trades concluded within the same month. Finally, because CDS contracts mostly trade with standardized maturities and fixed rates, we can control non-parametrically for the composition of contracts. The term $\sum_k \gamma_k * \mathbf{1}[maturity_i \in k]$ could include a full set of dummies for standardized CDS maturities, while the term $\sum_p \gamma p * \mathbf{1}[rate_i \in p]$ include dummies for standardized fixed rates. $\sum_r \gamma_r * \mathbf{1}[seniority_i \in r]$ account for the seniority of the reference obligation, while X_c are additional controls at contract and firm level, such as the logarithm of the notional amount and the rating score of the reference entity.

For the model explaining upfront prices, it is important to separate trades in function of their direction (whether the buyside investor sells or buy the CDS). This is the reason why we can only carry out this analysis on In fact, for client buy trades, the lower the upfront fee, the more advantageous the trade is for the buyer. For client sell trades, the higher the upfront fee the more advantageous the trade. Therefore, when a bank buys a CDS contract, and the β coefficient is negative (positive) then the bank is paying a lower (higher) price than non-bank investors, for similar contracts. In contrast, when a bank sells the CDS contract, and the β coefficient is positive (negative) then the bank is paying a lower (higher) price than non-bank investors, for similar contracts.

4.1.1 Price Impact

Next, we study whether there is any price impact following trades that dealers conclude with banks. We measure the price impact of bank privileged information at two different horizons: one week and one month. For this, we investigate whether there is any pricing bias on trades dealers conclude with non-bank investors, after trading with a bank, and on the same reference entity on which the transaction with the bank was concluded. If the dealer learned valuable private information after trading with the bank and if it compensated the bank for it, then we would expect the dealer to charge its subsequent clients less favourable prices. In this way, the dealer recovers the losses they made by trading with banks, and extracts higher information rents by trading with other non informed dealers or investors.

For this, we identify the trades dealers conclude with non bank clients on reference entities on which their previously concluded a trade with a bank, over the following week or month. We then compare their prices to those trades entered into with clients on reference entities on which the same dealer did not trade with a bank, over the past week of month. We again restrict the sample of transactions to the D2C set, and in particular to dealer versus non-bank investors, and we separate the estimations for buy and sell trades.

4.2 Analysis of Bid-Ask Spreads Paid by Banks

Next, we study the impact of trading with banks on transaction costs in the CDS market. For this, we use as a dependent variable the half bid ask spreads defined above. The estimation seek to identify whether the spreads dealers set when trading with banks are different (narrower or wider) than the spreads they charge non-bank investors.

$$|HalfSpread_{idft}| = \beta * \mathbf{1}[buyside_i \in bank] + \alpha_d + \theta X_c + \sum_k \gamma_k * \mathbf{1}[maturity_i \in k] + \\ + \sum_p \gamma_p * \mathbf{1}[coupon_i \in p] + \sum_r \gamma_r * \mathbf{1}[seniority_i \in r] + \epsilon_{idft}$$

In this model, the dependent variable, $|HalfSpread_{idft}|$, captures the absolute value of the realized half spread sold by dealer d to investor i, on reference entity f, at time t. As before, we control non-parametrically for the main contract features, parametrically for notionals trades and rating scores, and we add different fixed effects. Crucially, because we work with deviations from the upfront fees quoted by CDS dealers for the same contract, on the same day, our measure of pricing impact is robust with respect to daily changes in characteristics and risk profile of the underlying entities. In the most restricted specification, we add dealer $\times$ reference entity fixed effects to study whether spreads charged to banks are different from spreads charged to non-bank investors, when then same dealer transacts on the same reference with the two investor types.

Finally, because we work with deviations from the mid in absolute terms, there is no need to separate buy and sell trades for this estimations. As a result, we can employ the full sample of trades: dealer-to-dealer (D2D) and dealer-to-customer (D2C). A negative β would indicate that bid-ask spreads paid by banks are narrower than for the remaining investors, thus suggesting that banks are treated relatively more favourably by their dealers in terms of transaction costs. Conversely, a positive β would indicate that banks pay higher transaction costs relatively, and are thus penalized on the CDS market.

4.2.1 Price Impact

If dealers learn any private information from their trades with banks, then this information might be also reflected in the bid-ask spreads their set on subsequent trades. We therefore also study whether there is any bias in transaction costs following trades with banks. Again, we identify trades that a dealer concludes with non-bank counterparties over a one-week and one-month horizon. In this case, we can see whether any information appears to be transmitted to the spreads in the dealer market, as well as in the dealer to customer market. Plausibly, if dealers trade with banks in order to learn their private information and compensate these banks with narrower bid-ask spreads, then they might charge larger spreads on subsequent trades, in order to monetize this information.

5 Results

5.1 On the Overall Cost of Credit Risk

Table 1 already shows that, on average, banks pay relatively lower CDS upfront fees whenever they purchase CDS protection from dealers, and they receive relatively higher upfront fees whenever they sell CDS protection. The average upfront payment is 1% of notional for trades where the buyside is a bank purchasing protection, whereas dealer-to-dealer trades have an average upfront of 2%, and the average upfront in dealer-to-non bank trades is as high as 3%. Banks also receive higher payments whenever they are selling protection. A bank investor receives on average 3% of notional, compared to a 2% on the intra-dealer market, and 1% that non-bank protection sellers receive from their dealers. While these averages could be driven by compositional effects, regressions with comprehensive controls and fixed effects uphold theses findings.

Table 2 and Table 3 confirm that there is indeed a pricing bias in dealer-to-bank trades. Across the different specifications, banks are charged lower payments when they purchase protection, and are rewarded with higher payments when they sell protection. Because we need to sign the trades in order to observe these effects, the sample underlying these estimations is composed of D2C trades. On average and controlling for the main contract characteristics, banks pay upfront amounts lower by 2pp when purchasing protection, relative to non bank investors. The most restricted specification in Column (6), including dealer *times* issuer *times* month fixed effects, suggests that the same dealer selling the same CDS protection contract during the same month to a bank and a non-bank investor, will charge the bank an upfront lower by 1pp. The effects are weaker in magnitude, but still significant, for sell trades. A dealer buying the same CDS protection contract during the same month from a bank and from a non-bank investor, will pay the bank an upfront higher by 0.13pp. This suggests that banks are consistently better informed than dealers about changes in credit risk, and that dealers learn valuable information when trading with banks. In exchange, they reward banks for this information.

But is the private information then incorporated into transaction prices? Do dealers monetize this information? Table 4 and Table 5 show that dealers that become informed after trading with a bank then use this information when offering quotes to non-bank buyside investors. After selling CDS protection to a bank, a dealer will increase its price and sell protection more expensively to other investors, on the same reference entity. After purchasing CDS protection from a bank, a dealer will be buying protection at more favourable fees from non-bank investors. Thus non-bank protection sellers get paid less, relatively to banks. These effects are economically significant and broadly unchanged in specifications with dealer and dealer *times* industry fixed effects, when controlling for contract and reference entity characteristics, and they hold both a one week and one month horizons.

5.2 On Transaction Costs

Tables 6 and 7 focus on the transaction costs that banks pay when trading CDS. We measure transaction costs as the absolute half spreads (upfront payment on the contract minus benchmark quote). We find that banks enjoy a discount also in terms of the bid-ask spreads they pay. The analysis of the full sample of trades in Table 6 and of the D2C segment in Table 7 both reveal that bid-ask spreads are narrower by around 0.2 - 0.4 pp when the buyside investor is a bank. In fact, when banks purchase credit protection and therefore potentially reveal negative information about the underlying firm, they pay about 1.6% of notional less in total upfront payments, 25% of which amounts to savings in transaction costs.

Finally, Table 8 investigate how these effects vary with the credit quality of the reference entity. We group issuers in three categories, depending on their rating: prime or highly rated, medium grade, and speculative or without rating. We find that the effect is concentrated in the last group, which suggests that bank information is more important whenever the underlying firm is riskier.

6 Conclusion

We use the CDS transaction level dataset available at the European Central Bank to study whether banks are able to trade derivatives on corporate borrowers at the same prices as non-bank buyside investors. Overall, our findings suggest that banks can purchase CDS protection on more affordable terms than non-bank investors. This is consistent with banks holding and monetizing private borrower information. Because it is relatively cheap, the derivative can be particularly useful in bank risk management practices, and it can help transmitting valuable information from banks to the rest of the financial market.

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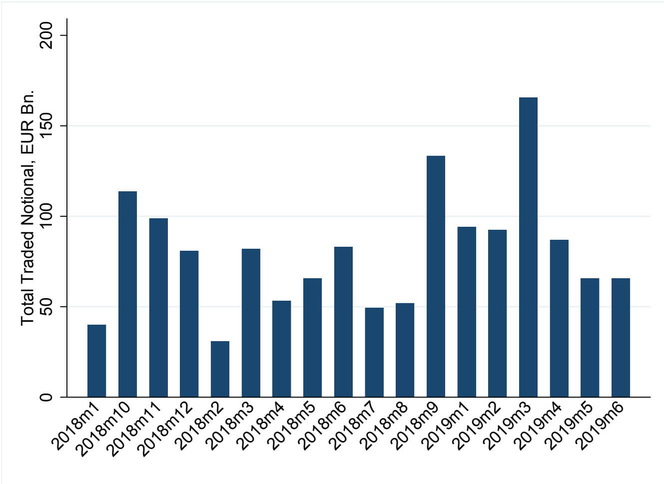
A. FIGURES

Panel A. Total CDS Trading - Volumes



Panel B. Total CDS Trading by Market Segment - Volumes

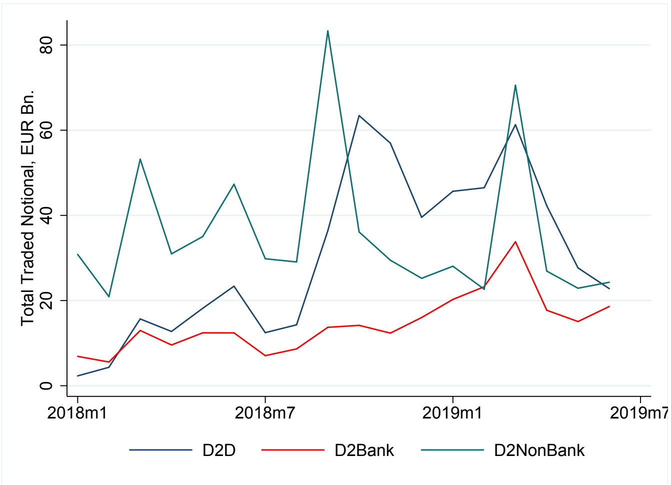
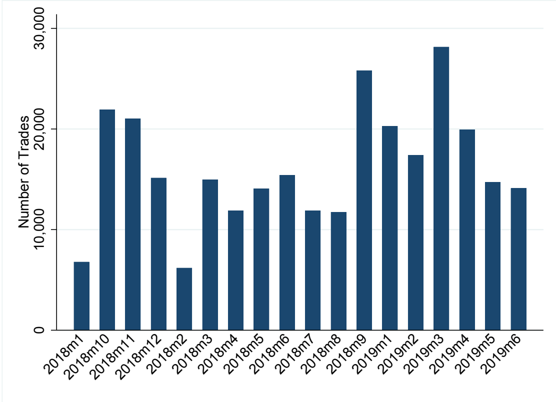


Figure 1: . Total CDS Notional

This figure shows total CDS trading across our final sample of 291,591 trades. Panel A shows monthly totals, while Panel B decomposes these volumes by market segment: dealer-to-dealer (D2D), dealer-to-bank investor (D2Bank), and dealer-to-non bank investor (D2NonBank)

Panel A. Total CDS Trading - Number of Trades



Panel B. Total CDS Trading by Market Segment - Number of Trades

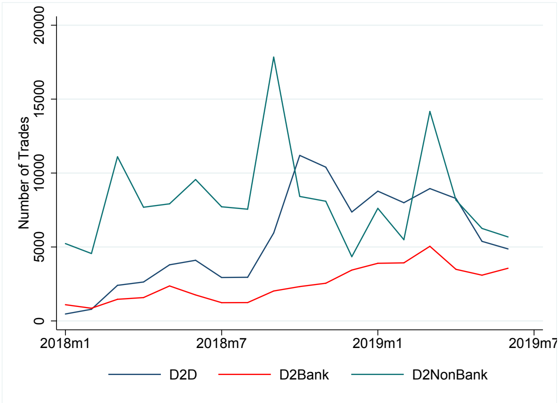
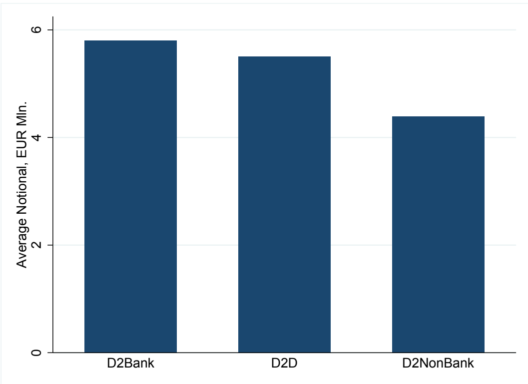
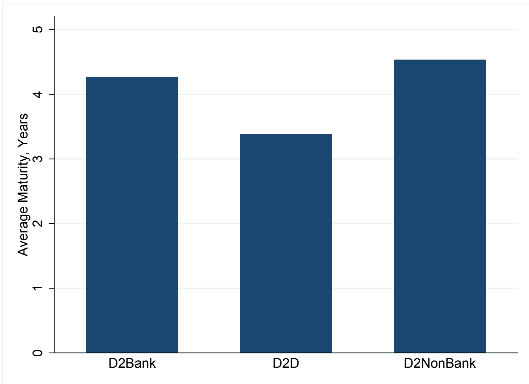


Figure 2: . Total Number of Trades

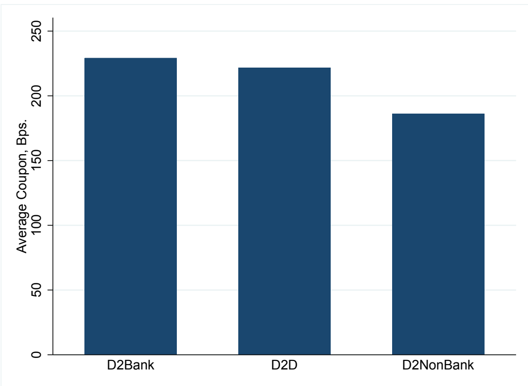
This figure shows the total number of CDS contracts traded monthly, across our final sample of 291,591 trades. Panel A shows monthly totals, while Panel B decomposes the aggregated trade count by market segment: dealer-to-dealer (D2D), dealer-to-bank investor (D2Bank), and dealer-to-non bank investor (D2NonBank)



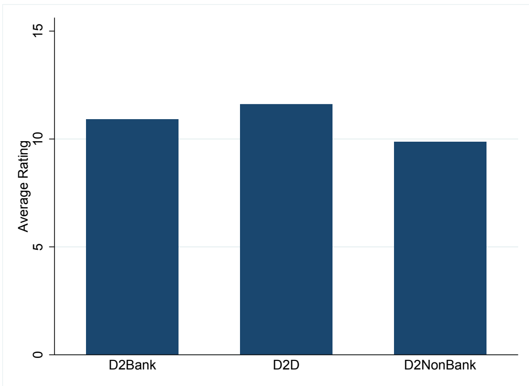
(a) Average Notional



(b) Average Tenor



(c) Average Coupon



(d) Average Rating

Figure 3: Main CDS Contract Characteristics by Market Segment

The four figures compare average characteristics of CDS contracts (notional, tenor, coupons and issuer rating) across market segments: dealer-to-dealer (D2D), dealer-to-bank investor (D2Bank), and dealer-to-non bank investor (D2NonBank)

B. TABLES

Table 1: . Summary Statistics: Trade Characteristics

	N	Mean	SD	P25	P50	P75
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Intradealer Market (D2D)						
Upfront Fee (=Upfront Payment:Notional)	99,236	2.02	6.86	-0.73	1.11	3.67
Notional (EUR Million)	99,236	5.50	9.72	1.50	3.75	5.50
Coupon	99,236	221.79	184.08	100.00	100.00	500.00
Seniority (1=Senior; 2=Subordinate)	99,236	1.00	0.02	1.00	1.00	1.00
Tenor (in Years)	99,236	3.38	1.99	2.00	4.00	5.00
Rating Score	99,236	11.62	5.63	8.00	10.00	15.00
Dealer-to-Customer Market (D2C) - Buy Trades - Dealer to Bank						
Upfront Fee (=Upfront Payment:Notional)	21,850	0.84	7.83	-2.18	0.80	2.99
Notional (EUR Million)	21,850	6.03	12.90	2.00	4.30	5.50
Coupon	21,850	236.02	189.49	100.00	100.00	500.00
Seniority (1=Senior; 2=Subordinate)	21,850	1.36	0.48	1.00	1.00	2.00
Tenor (in Years)	21,850	4.08	1.66	3.00	5.00	4.00
Rating Score	21,850	11.07	5.21	7.00	9.00	14.00
Dealer-to-Customer Market (D2C) - Buy Trades - Dealer to Non Bank						
Upfront Fee (=Upfront Payment:Notional)	78,028	2.59	7.33	-0.21	1.69	3.98
Notional (EUR Million)	78,028	4.43	32.70	0.45	1.58	5.00
Coupon	78,028	189.57	166.75	100.00	100.00	100.00
Seniority (1=Senior; 2=Subordinate)	78,028	1.43	0.49	1.00	1.00	2.00
Tenor (in Years)	78,028	4.59	1.19	5.00	5.00	5.00
Rating Score	78,028	9.85	3.89	8.00	9.00	11.00
Dealer-to-Customer Market (D2C) - Sell Trades - Dealer to Bank						
Upfront Fee (=Upfront Payment:Notional)	23,083	2.51	6.98	0.04	1.71	3.85
Notional (EUR Million)	23,083	5.58	12.10	2.00	3.10	5.00
Coupon	23,083	222.96	184.57	100.00	100.00	500.00
Seniority (1=Senior; 2=Subordinate)	23,083	1.33	0.47	1.00	1.00	2.00
Tenor (in Years)	23,083	4.44	1.69	4.00	5.00	5.00
Rating Score	23,083	10.78	5.28	7.00	9.00	14.00
Dealer-to-Customer Market (D2C) - Sell Trades - Dealer to Non Bank						
Upfront Fee (=Upfront Payment:Notional)	69,394	1.42	7.36	-1.54	1.19	3.25
Notional (EUR Million)	69,394	4.34	11.20	0.48	1.71	5.00
Coupon	69,394	182.60	161.92	100.00	100.00	100.00
Seniority (1=Senior; 2=Subordinate)	69,394	1.48	0.50	1.00	1.00	2.00
Tenor (in Years)	69,394	4.47	1.34	5.00	5.00	5.00
Rating Score	69,394	9.88	3.91	8.00	9.00	11.00

This table reports summary statistics for the 291,591 CDS contracts in the final sample, over the period January 2018 to June 2019. The sample is spilt into different market segments: dealer - to - dealer (D2D) and dealer - to - customer (D2C) trades, as well as, for the latter category, based on trade direction and on whether the buyside investor is a bank or not.

Table 2: . Analysis of Upfront Prices Paid by Banks (I)

Dependent Variable	Upfront Price Points = Upfront Payment/Notional					
Sample	**D2C Market - Buy Trades**					
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}_{\text{Buyside Investor is Bank}}$	-0.0219***	-0.0196***	-0.0181***	-0.0126***	-0.0161***	-0.0114***
	(0.0005)	(0.0006)	(0.0006)	(0.0006)	(0.0005)	(0.0006)
Contract Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Issuer Rating	Yes	Yes	Yes	Yes	Yes	Yes
Dealer FE	-	Yes	Yes	Yes	-	-
Industry × Month FE	-	-	Yes	-	-	-
Issuer × Month FE	-	-	-	Yes	-	-
Dealer × Issuer FE	-	-	-	-	Yes	-
Dealer × Issuer × Month FE	-	-	-	-	-	Yes
Observations	99,878	99,878	98,878	99,878	99,878	99,878
R^2	0.100	0.112	0.153	0.434	0.472	0.657

This table reports the coefficients of OLS estimations where the unit of observation is a trade, at dealer - counterparty - reference entity level. The dependent variable is the transaction price, expressed as the ratio between the upfront payment exchanged by the two parties, and the traded notional. The period of analysis is January 2018 to June 2019, the segment is the dealer-to-customer (D2C) market, and the trades are all buy (i.e., the buyside investor buys CDS protection). The main explanatory variable, $\mathbb{1}_{\text{Buyside Investor is Bank}}$, takes value 1 when the buyside investor is a bank, and 0 otherwise. Contract characteristics include standardized maturities and coupons, the seniority of the reference obligation (senior or subordinate), and the logarithm of the traded notional. Issuer rating is a linear function of the rating of the reference firm, as classified by one of the top three rating agencies. ${}^{\star}p < 0.10, {}^{\star\star}p < 0.05, {}^{\star\star\star}p < 0.01$

Table 3: . Analysis of Upfront Prices Paid by Banks (II)

Dependent Variable	Upfront Price Points = Upfront Payment/Notional					
Sample	**D2C Market - Sell Trades**					
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}_{\text{Buyside Investor is Bank}}$	0.0014***	0.0043***	0.0020***	0.0049***	0.0036***	0.0013**
	(0.0005)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Contract Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Issuer Rating	Yes	Yes	Yes	Yes	Yes	Yes
Dealer FE	-	Yes	Yes	Yes	-	-
Industry × Month FE	-	-	Yes	-	-	-
Issuer × Month FE	-	-	-	Yes	-	-
Dealer × Issuer FE	-	-	-	-	Yes	-
Dealer × Issuer × Month FE	-	-	-	-	-	Yes
Observations	92,477	92,477	92,477	92,477	92,477	92,477
R^2	0.110	0.129	0.438	0.165	0.515	0.672

This table reports the coefficients of OLS estimations where the unit of observation is a trade, at dealer - counterparty - reference entity level. The dependent variable is the transaction price, expressed as the ratio between the upfront payment exchanged by the two parties, and the traded notional. The period of analysis is January 2018 to June 2019, the segment is the dealer-to-customer (D2C) market, and the trades are all sell (i.e., the buyside investor sells CDS protection). The main explanatory variable, $\mathbb{1}_{\text{Buyside Investor is Bank}}$, takes value 1 when the buyside investor is a bank, and 0 otherwise. Contract characteristics include standardized maturities and coupons, the seniority of the reference obligation (senior or subordinate), and the logarithm of the traded notional. Issuer rating is a linear function of the rating of the reference firm, as classified by one of the top three rating agencies. $^{\star}p < 0.10,^{\star\star}p < 0.05,^{\star\star\star}p < 0.01$

Table 4: . Price Impact on Non Bank Investors (I)

Dependent Variable	Upfront Price Points = Upfront Payment/Notional					
Sample	**D2C Market - Buy Trades**					
	(1)	(2)	(3)	(4)	(5)	(6)
1-Week Impact	0.0044***		0.0040***		0.0021***	
	(0.0006)		(0.0006)		(0.0006)	
1-Month Impact		0.0054***		0.0060***		0.0037***
		(0.0005)		(0.0005)		(0.0005)
Contract Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Issuer Rating	Yes	Yes	Yes	Yes	Yes	Yes
Dealer FE	-	-	Yes	Yes	Yes	Yes
Industry × Month FE	-	-	-	-	Yes	Yes
Observations	78,028	78,028	78,028	78,028	78,028	78,028
R^2	0.127	0.126	0.144	0.144	0.189	0.190

This table reports the coefficients of OLS estimations where the unit of observation is a trade, at dealer - counterparty - reference entity level. The dependent variable is the transaction price, expressed as the ratio between the upfront payment exchanged by the two parties, and the traded notional. The period of analysis is January 2018 to June 2019, the segment is the dealer-to-customer (D2C) market, and the trades are all buy (i.e., the buyside investor buys CDS protection). The sample only includes trades with non-bank buyside investors. The main explanatory variables, 1-Week Impact and 1-Month Impact, take value 1 when the trade follows a trade that the same dealer conducts with a bank within the last week (respectively, month), and 0 otherwise. Contract characteristics include standardized maturities and coupons, the seniority of the reference obligation (senior or subordinate), and the logarithm of the traded notional. Issuer rating is a linear function of the rating of the reference firm, as classified by one of the top three rating agencies. $^{\star}p < 0.10, ^{\star\star}p < 0.05, ^{\star\star\star}p < 0.01$

Table 5: . Price Impact on Non Bank Investors (II)

Dependent Variable	Upfront Price Points = Upfront Payment/Notional					
Sample	**D2C Market - Sell Trades**					
	(1)	(2)	(3)	(4)	(5)	(6)
1-Week Impact	-0.0062***		-0.0054***		-0.0034***	
	(0.0007)		(0.0007)		(0.0007)	
1-Month Impact		-0.0056***		-0.0050***		-0.0027***
		(0.0006)		(0.0006)		(0.0006)
Contract Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Issuer Rating	Yes	Yes	Yes	Yes	Yes	Yes
Dealer FE	-	-	Yes	Yes	Yes	Yes
Industry × Month FE	-	-	-	-	Yes	Yes
Observations	69,394	69,394	69,394	69,394	69,394	69,394
R^2	0.121	0.143	0.180	0.121	0.144	0.180

This table reports the coefficients of OLS estimations where the unit of observation is a trade, at dealer - counterparty - reference entity level. The dependent variable is the transaction price, expressed as the ratio between the upfront payment exchanged by the two parties, and the traded notional. The period of analysis is January 2018 to June 2019, the segment is the dealer-to-customer (D2C) market, and the trades are all sell (i.e., the buyside investor sells CDS protection). The sample only includes trades with non-bank buyside investors. The main explanatory variables, 1-Week Impact and 1-Month Impact, take value 1 when the trade follows a trade that the same dealer enters with a bank within the last week (respectively, month), and 0 otherwise. Contract characteristics include standardized maturities and coupons, the seniority of the reference obligation (senior or subordinate), and the logarithm of the traded notional. Issuer rating is a linear function of the rating of the reference firm, as classified by one of the top three rating agencies. $^{\star}p < 0.10$,$^{\star\star}p < 0.05$,$^{\star\star\star}p < 0.01$

Table 6: . Analysis of Bid-Ask Spreads Paid by Banks (I)

Dependent Variable	Absolute Half Spreads					
Sample	**D2D + D2C Market, All Trades**					
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}_{\text{Buyside Investor is Bank}}$	-0.0002 (0.0005)	-0.0012*** (0.0005)	-0.0018*** (0.0005)	-0.0020*** (0.0005)	-0.0029*** (0.0005)	-0.0008* (0.0004)
Contract Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Issuer Rating	Yes	Yes	Yes	Yes	Yes	Yes
Dealer FE	-	Yes	Yes	Yes	-	-
Industry FE	-	-	Yes	-	-	-
Month FE	-	-	Yes	-	Yes	-
Industry × Month FE	-	-	-	Yes	-	-
Dealer × Industry FE	-	-	-	-	Yes	-
Dealer × Issuer FE	-	-	-	-	-	Yes
Observations	184,955	184,955	184,955	184,955	184,955	184,955
R^2	0.35	0.36	0.38	0.38	0.38	0.77

This table reports the coefficients of OLS estimations where the unit of observation is a trade, at dealer - counterparty - reference entity level. The dependent variable is the absolute value of the half-bid ask spread, expressed as the difference between the transaction price of the contract, and the quote mid for the same reference firm, maturity, coupon, and seniority. The period of analysis is January 2018 to June 2019, and the sample includes all trades for which there was a matching mid (D2D and D2C segments, as well as both buy and sell trades). The main explanatory variable, $\mathbb{1}_{\text{Buyside Investor is Bank}}$, takes value 1 when the buyside investor is a bank, and 0 otherwise. Contract characteristics include standardized maturities and coupons, the seniority of the reference obligation (senior or subordinate), and the logarithm of the traded notional. Issuer rating is a linear function of the rating of the reference firm, as classified by one of the top three rating agencies. $^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$

Table 7: . Analysis of Bid-Ask Spreads Paid by Banks (II)

Dependent Variable	Absolute Half Spreads					
Sample	**D2C Market, All Trades**					
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}_{\text{Buyside Investor is Bank}}$	-0.0028***	-0.0024***	-0.0045***	-0.0049***	-0.0053***	-0.0040***
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0005)
Contract Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Issuer Rating	Yes	Yes	Yes	Yes	Yes	Yes
Dealer FE	-	Yes	Yes	Yes	-	-
Industry FE	-	-	Yes	-	-	-
Month FE	-	-	Yes	-	Yes	-
Industry × Month FE	-	-	-	Yes	-	-
Dealer × Industry FE	-	-	-	-	Yes	-
Dealer × Issuer FE	-	-	-	-	-	Yes
Observations	101,677	101,677	101,677	101,677	101,677	101,677
R^2	0.38	0.39	0.40	0.42	0.42	0.72

This table reports the coefficients of OLS estimations where the unit of observation is a trade, at dealer - counterparty - reference entity level. The dependent variable is the absolute value of the half-bid ask spread, expressed as the difference between the transaction price of the contract, and the quote mid for the same reference firm, maturity, coupon, and seniority. The period of analysis is January 2018 to June 2019, and the sample includes all D2C trades for which there was a matching mid, thus including both buy and sell trades). The main explanatory variable, $\mathbb{1}_{\text{Buyside Investor is Bank}}$, takes value 1 when the buyside investor is a bank, and 0 otherwise. Contract characteristics include standardized maturities and coupons, the seniority of the reference obligation (senior or subordinate), and the logarithm of the traded notional. Issuer rating is a linear function of the rating of the reference firm, as classified by one of the top three rating agencies. $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$

Table 8: . Effects by Rating Group

Dependent Variable	Absolute Half Spreads		
Sample	**D2D + D2C Market, All Trades**		
	High Grade	Medium Grade	Speculative and No Rating
	(1)	(2)	(3)
$\mathbb{1}_{\text{Buyside Investor is Bank}}$	0.0001	0.0006	-0.0048***
	(0.0007)	(0.0004)	(0.0012)
Contract Characteristics	Yes	Yes	Yes
Issuer Rating	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
Dealer × Industry FE	Yes	Yes	Yes
Observations	6,622	111,834	60,494
R^2	0.32	0.49	0.35

This table reports the coefficients of OLS estimations where the unit of observation is a trade, at dealer - counterparty - reference entity level. The dependent variable is the absolute value of the half-bid ask spread, expressed as the difference between the transaction price of the contract, and the quote mid for the same reference firm, maturity, coupon, and seniority. The period of analysis is January 2018 to June 2019, and the sample includes all trades for which there was a matching mid (D2D and D2C segments, including both buy and sell trades). The main explanatory variable, $\mathbb{1}_{\text{Buyside Investor is Bank}}$, takes value 1 when the buyside investor is a bank, and 0 otherwise. Contract characteristics include standardized maturities and coupons, the seniority of the reference obligation (senior or subordinate), and the logarithm of the traded notional. Column (1) restricts the sample to reference entities with a "high grade" or "prime" rating, column (2) captures reference entities rated "upper medium grade" or "lower medium grade", whiles column (3) shows the effects on references rated "speculative", "highly speculative", or without rating. Issuer ratings follow the classification of the top three rating agencies. ${}^{\star}p < 0.10, {}^{\star\star}p < 0.05, {}^{\star\star\star}p < 0.01$

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